The long and variable lags of monetary policy: Evidence from disaggregated price indices*

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Abstract

We study how monetary policy affects subcomponents of the Personal Consumption Expenditures Price Index (PCEPI). Using local projections, we estimate impulse response functions of these subcomponents to identified shocks to the target Fed Funds Rate. Following a monetary policy contraction, the aggregate PCEPI turns significantly negative after over three years. This dynamic masks stark differences in timing and magnitude of the responses across price categories. Important categories, such as gasoline and used motor vehicles, respond negatively after a long delay or even a positive initial response, while others, such as clothing, fall more rapidly. It is only at horizons of several years that the price decline is broad-based across categories. We discuss theoretical interpretations of our findings and point to useful directions for future theoretical research. We also show how to re-aggregate our cross-sectional estimates and their standard errors, taking into account dependence between different prices using a Seemingly Unrelated Regression approach. This procedure allows us to construct hypothetical PCEPI responses to monetary policy using counterfactual consumption expenditure shares. We find that the price level response re-aggregated using the 2023 expenditure shares displays a similar long-lagged profile as the actual PCEPI. This result indicates that changes in expenditure behavior have not accelerated the long-lagged response of inflation to monetary policy.

Keywords: Monetary policy; Federal Reserve; Price indices; Local projections
JEL Classification: C10; E31; E52; E58.

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1 Introduction

How monetary policy affects prices is a classic question in macroeconomics. It has gained new impetus after the inflation surge and sharp tightening in monetary policy by the Federal Reserve beginning in 2022. In most macro models, changes in monetary policy result in both a delayed and a less than one-to-one pass-through to prices. Empirical work on the question yields a range of results on the length of this delay and the size of the pass-through, leaving considerable uncertainty around the question of how long it takes for inflation to come back to target. Fed Chair Powell emphasized in his 2023 Jackson Hole speech that the Fed's "*assessment is further complicated by uncertainty about the duration of the lags with which monetary tightening affects (...) especially inflation.*"

This paper sheds new light on this question by studying the responses of disaggregated price series to interest rate changes. Our premise is that a cross-sectional price analysis helps unpack the effect of monetary policy on inflation. If different prices display a different time lag in their peak response, for example, the aggregate series will likely mask this heterogeneity and thus be silent about a potentially important feature of the monetary transmission mechanism. Furthermore, the importance of different price series in aggregate price indices keeps changing, which might alter the transmission of monetary policy through time. Our starting point takes inspiration from a rich literature that uses micro-level price data for macroeconomic questions, e.g. Nakamura and Steinsson (2008).

Our focus lies on the dynamics of subcomponents of the Personal Consumption Expenditure Price Index (PCEPI). The motivation for this choice is twofold. First, the PCEPI is the price measure targeted by the Fed, so it is naturally of interest for monetary policy research. Second, the PCEPI can be disaggregated in a way that is relatively consistent through time. The Bureau of Economic Analysis (BEA) provides the PCEPI data at several levels of disaggregation. For example, the roughest level of disaggregation splits prices into prices of goods and services. The finest level of disaggregation that we study in our analysis includes the prices of, for example, corrective eyeglasses and contact lenses, electric appliances for personal care, dental services, or water transportation.

Methodologically, we use local projections (Jordà, 2005) to estimate impulse response functions (IRFs) of different prices to identified exogenous shocks to the target Federal Funds Rate (FFR). While the aggregate price level is the subject of most previous IRF analyses, we employ a large number local projections to different levels of price level disaggregation. We use the identified monetary policy shock series of Aruoba and Drechsel (2023) to analyze plausibly exogenous interest rates changes. We focus on the 1982 to 2008 sample during which the Fed targeted the FFR and non-standard monetary policy was not used as a main tool. Our choice of the shock series and sample allows us to draw a connection to monetary policy in 2022 and 2023, which was arguably conducted through "traditional" interest hikes, in the same spirit as those in the pre-zero lower bound period.

Furthermore, we develop a re-aggregation procedure for our cross-sectional IRF estimates and their standard errors. The responses of different prices to monetary policy are not independent from each other in most macroeconomic models. To take into account this dependence econometrically we propose a Seemingly Unrelated Regression (SUR) approach to a system of local projections. We estimate this system via Feasible Generalized Least Squares (FGLS) and obtain covariance estimates across price responses. These covariance estimates are needed to correctly compute standard errors of any re-aggregated IRF. Our SUR approach is a technical contribution to the literature on inference with local projections, which we survey further below. The approach could be relevant for other applications in which disaggregated local projections are constructed and aggregation is desired, for example in household-level or firm-level local projections.

Our re-aggregation procedure allows us to draw inference about a hypothetical aggregate PCEPI responses to a monetary policy change assuming different actual or hypothetical expenditure shares, such as the expenditure shares over the full sample or those at specific points in history. One experiment that is of particular interest is re-aggregation using the latest expenditure shares. Comparing this response to the response of the actual PCEPI itself will be informative about whether changing expenditure shares, e.g. due to structural change, have accelerated or decelerated the response of inflation to a change in monetary policy.

Our findings are as follows. First, after a monetary policy contraction, the headline PCEPI displays a gradual decline, turning significantly negative at conventional levels only after 43 months, that is, more than three years. The peak reduction occurs after 54 months and our point estimate amounts to a roughly 4% lower price level after a 100 basis point monetary policy contraction. We estimate a very similar timing for the response of the core PCEPI, which excludes food and energy. The magnitude of the response of the core PCEPI is smaller, with a point estimate that implies a 2.5% price level reduction after a 100 basis point tightening. The lagged response echoes existing findings from the literature. For example, in Christiano, Eichenbaum, and Evans (1999), the aggregate price level does not fall to a statistically significant extent for 4 years after an FFR increase.

Second, the aggregate response masks stark differences across individual price categories. After a monetary policy contraction, some price categories respond negatively after a long delay or even a positive initial response, while others fall more rapidly. For example, we find that important categories such as gasoline and used motor vehicles respond negatively after a long delay. For some components, the initial response to an interest rate increase is even positive. Other categories, such as clothing and footwear, fall more rapidly after a contractionary shock. Many categories do not respond across the entire horizon we consider. One insight of this finding is that the reason why the headline and core PCEPI IRF is flat for several years is *not* because all prices are unchanged. On the contrary, many of them change but both positive responses and different turning points make it hard to get a clean negative response in the aggregate until enough of the series start falling. It is only at a horizon of more than three years that the decline is broad-based across prices.

As part of our analysis of individual price components, we show that it is relevant to construct IRFs for both the level response of individual prices, as well as the cumulated contribution of each price to the total PCEPI. The latter analysis allows us to understand the role of the initial contribution of a given price, the change in the contribution in response to the shock and the response of the price to the shock. The contribution analysis makes clear that the PCEPI response to monetary policy tends to be driven by just a handful of important categories.

Third, we provide interpretations of our cross-sectional results in light of theories of price adjustment. For example, the positive, negative and many flat price responses to a monetary tightening at short horizons, and a broad-based decline in prices at long horizons, cannot be rationalized with a Calvo model. We examine the empirical relationship between the peak response of our IRF estimates and the price adjustment frequency estimates across PCEPI categories of Carvalho, Lee, and Park (2021). We find that the strong negative relationship that would be suggested by Calvo pricing is not present in our results. Menu cost models and various theories of information frictions also cannot generate the IRF patterns across different prices we estimate. We speculate that theories with a heterogeneous cost channel of interest rates are a possible theoretical rationalization for our results. A monetary policy tightening could constrain the supply of goods and services by firms with financial constraints that tighten when nominal interest rates rise. In that way, monetary policy shocks could act as demand shocks to some sectors but supply shocks to other sectors in the short run, with the aggregate demand force eventually dominating across sectors at longer horizons.

Fourth, the SUR-based re-aggregation of our individual IRFs, using the latest expenditure shares, shows that the price level falls with a similar timing and magnitude than estimated with the aggregate series itself. The pattern is similar for both the headline and the core CPE. We find this to be the case when we re-aggregate IRF estimates based on rougher or finer levels of disaggregation. This result means that changes in expenditure shares, e.g. because of structural change, have not accelerated the response of the PCEPI to monetary policy. We further interpret this result by analyzing changes in consumer behavior. The most marked changes in expenditure shares that have happened over the last decades are a decrease in the share for food and beverages (-12 percentage points) and an increase for health care (+11). Both categories respond to monetary policy with a long lag. What we cannot rule out with our methodology and data is that price stickiness across all or important categories has declined, which could accelerate the response. However, health care services are among the most sticky and least cyclically sensitive price categories (Stock and Watson, 2020; Carvalho, Lee, and Park, 2021).

Taken together, our results echo the famous insight of Friedman (1960) that "*there is much evidence that monetary changes have their effect only after a considerable lag and over a long period and that the lag is rather variable.*"[1] We find that the idea of *long* lags in the transmission of monetary policy is substantial. We also find large differences in the timing of the response across different variables, which we point out are *variable* lags in the cross-section of prices. A corollary of our conclusions is that the price effect of the 2022-23 rate hikes might take up to 2026 or 2027 to be fully reflected in the data. We discuss potential mechanisms through which a faster response than suggested by our estimates might have occurred, by inspecting state-dependence and asymmetries in our local projection setup.

[1]The idea is further examined in Friedman (1961). An interesting review of the origin of the term "long and variable lags" is provided by Dupor (2023).

Literature. Our work connects to three strands of research. The first literature estimates the effects of monetary policy, in particular using identified monetary policy shocks. A survey on different findings and methodologies is contained in the handbook chapter by Ramey (2016). Recent examples are Aruoba and Drechsel (2023) and Bauer and Swanson (2022).

The second literature spans work in macroeconomics that uses disaggregated (or micro-level) price data, with Nakamura and Steinsson (2008) being an influential example. Comprehensive surveys are provided by Klenow and Malin (2010) and Nakamura and Steinsson (2013). Some papers in this second literature intersect with the first literature on constructing IRFs to monetary policy shocks. An early approach in this direction Bernanke, Boivin, and Eliasz (2005) who employ a factor-augmented vector autoregression (FAVAR) approach to construct IRFs of a large number of macroeconomic time series, including a few subcomponents of both the consumer price and producer price index. Boivin, Giannoni, and Mihov (2009) extend the FAVAR approach to include a much larger set of price series, and Baumeister, Liu, and Mumtaz (2013) additionally introduce time-variation in a FAVAR. They find that over time fewer prices exhibit a positive response to a monetary tightening and that there is a decline in the dispersion of disaggregated price responses. While we do not focus on time-varying responses, we show that both positive responses as well as dispersion among different price responses is still significant according to our analysis. Bils, Klenow, and Kryvtsov (2003) use a VAR approach to separately study the response of sticky and flexible price categories of goods, linking their analysis directly empirical work on price stickiness à la Bils and Klenow (2004). Balke and Wynne (2007) use 600 8-digit PPI price series to study the disaggregated effect of monetary policy shocks in a recursively identified VAR. Different from all aforementioned papers, we use local projections instead of (FA)VARs. Luo and Villar (2023) estimate IRFs to identified monetary policy shocks using local projection and relate them to price adjustment frequencies. Guerrieri, Marcussen, Reichlin, and Tenreyro (2023) look at responses of individual prices to monetary policy and oil supply shocks.[2] Buda et al. (2023) study responses to

[2]Interestingly, their responses are much more rapid than ours. We suspect this is due to the different sample and shock measure. Guerrieri, Marcussen, Reichlin, and Tenreyro (2023) use a monetary policy measure based on high-frequency surprises during a sample that includes the zero-lower bound period. As a consequence, their results likely pick up nonstandard monetary policy, which we attempt to exclude with our explicit focus on traditional interest rate policy.

monetary policy shocks of data that is disaggregated as well as at high frequency.[3] In a recent Bank for International Settlements report, Borio et al. (2021) also aggregate IRFs of individual PCEPI subcomponents, but as far as we know they do not account for cross-sectional dependence in the econometric inference.

The third literature we contribute to is concerned with econometric inference using local projections. Important contributions include Jordà (2005), Plagborg-Moller and Wolf (2021) and Montiel Olea and Plagborg-Moller (2021).[4] A survey is provided by Jordà (2023). We contribute to this literature by proposing a system estimator that takes into account dependence between cross-sectional local projection estimates, using a SUR and FGLS approach.[5] To the best of our knowledge, this has not been done in a local projection setting. Our SUR approach is different from the way panel local projections have typically been applied in the recent macro literature (see Almuzara and Sancibrián (2024) for a survey and technical treatment), because we assume a different response to a macro shock for each price, instead of a common coefficient in the cross-section.

2 Methodology

This section presents our methodology. We discuss the choice of data, estimation sample and econometric specification.

2.1 Data and sample

Price series. We focus on the PCEPI because it is the price measure targeted by the Federal Reserve and because can be disaggregated in a way that is relatively

[3]Buda et al. (2023) provide evidence of significant effects of monetary policy at very short horizons. Their analysis focuses on activity data, including consumption, sales and employment. It would be interesting to also consider high-frequency variation for prices, but this is not feasible with the PCEPI data provided by the BEA. Interesting work on collecting high-frequency price data is done by Cavallo and Rigobon (2016).

[4]Local projections have also been estimated with Bayesian approaches, see Ferreira, Miranda-Agrippino, and Ricco (2023) and Barnichon and Brownlees (2019).

[5]Our FGLS estimation relates to other approaches to estimating local projections using FGLS. For example, Lusompa (2023) proposes FGLS as a way to account for serially correlated errors in individual local projections, as an alternative to adjusting standard errors to be heteroskedasticity- and autocorrelation-consistent (HAC). Tanaka (2020) stacks the local projections for an individual variable across horizons and treats them as a multivariate regression (SUR) system with correlated residuals. Both approaches are different from our SUR/GLS approach because they are still an approach to the local projection for one variable and not a cross-section of variables.

consistent through time.[6] We retrieve the aggregate PCEPI and subcategories at different disaggregation levels from the BEA. The roughest level of disaggregation ('level 1') splits the index into 2 categories, goods and services. The next level ('level 2') splits it into 4 categories, durable goods, nondurable goods, services and consumption expenditures of nonprofit institutions serving households.[7] 'Level 3' of disaggregation contains 17 prices series, for example motor vehicles and parts or health care. 'Level 4' contains 70 categories, for example used motor vehicles or hospital and nursing home services. We go up to 'level 5' of disaggregation, with 136 price categories, including used light trucks or nursing homes.[8] A detailed overview of these different disaggregation levels is provided in the Online Appendix.

Monetary policy shocks. We use the identified monetary policy shocks provided by Aruoba and Drechsel (2023). The methodology to estimate these shocks is based on natural language processing and machine learning techniques, applied to the Fed's Greenbook (Tealbook) documents, following Romer and Romer (2004). Aruoba and Drechsel (2023) back out exogenous variation in the target FFR. The methodology is not based on using surprise changes in market interest rates, as is done in related literature, which might also reflect information effects or effects of nonstandard monetary policy.

Sample. We focus on the 1982 to 2008 sample during which the Fed targeted the FFR and non-standard monetary policy was not used as the main tool. Our choice of the sample period as well the type of monetary policy shock series allows us to draw a connection to monetary policy in 2022 and 2023, which was arguably conducted mainly through "traditional" interest hikes, in the same spirit as those in the pre-zero lower bound period.[9]

[6]Disaggregation through time is more challenging for the Consumer Price Index (CPI), where the set of subcategories is more unbalanced. Nevertheless, there is also a fairly strong overlap between PCEPI and CPI.

[7]We will omit this fourth category in most of our analysis, because it carries a low weight in aggregate indices and is slightly more difficult to interpret than other subcomponents.

[8]We do not go finer than level 5 because it it is not possible at those levels of disaggregation to split the index in a way that is balanced through time.

[9]During 2022 and 2023 the Fed also reduced the size of its balance through quantitative tightening. Arguably, this was done in a very gradual manner and the Fed' main policy tool was again the FFR. Indeed, Wright (2022) argues that the balance sheet shrinkage beginning in 2022 is likely to be gradual and unlikely to have large macroeconomic effects.

2.2 Local projections for price subcomponents

We construct IRFs using local projections (Jordà, 2005). While the aggregate price level is the subject of most previous IRF analyses, we employ local projections to different levels of disaggregation of the price level. Specifically, for each PCEPI subcomponent $i = 1, \ldots, N$, where N depends on the level of disaggregation, we run the following regression separately for each horizon $h = 0, ..., H$:

$$\log p_{i,t+h} = \alpha_{i,h} + \beta_{i,h}\hat{\varepsilon}_t^m + \gamma_{i,h}X_{i,t} + \delta_{i,h}\log p_{i,t-1} + u_{i,t+h}^h, \tag{1}$$

where $t = 1, \ldots, T$ indexes the observations through time. $\hat{\varepsilon}_t^m$ denotes the identified monetary policy shock. The estimate of $\beta_{i,h}$ represents the IRF of price category i at horizon h to the monetary policy shock. $X_{i,t}$ collects additional controls. As we run the local projection in (log) levels, we always include the first lag of the left-hand-side variable, that is, $\log p_{i,t-1}$. Including lags also helps to account for serially correlated errors, as shown by Montiel Olea and Plagborg-Moller (2021). We further discuss the issue of serially correlated errors below.

Selection of controls. In principle, $\hat{\varepsilon}_t^m$ is an exogenous regressor, so it is not required for correct identification of $\beta_{i,h}$ that controls $X_{i,t}$ are included. However, in small samples, the choice of the controls can matter for the precision of the estimates (see also Plagborg-Moller and Wolf (2021)). This might especially be the case for some PCEPI subcomponents, some of which are noisy times series. We therefore use a statistical model selection procedure to select controls among a set of macroeconomic variables and each variable's first 12 lags.[10] For each subcomponent i, in addition to a constant, one lag of the left hand side variable, we choose a set of up to 7 control variables that maximizes the fit of the regression at a year horizon ($h = 24$), using a combinatorial approach. This approach amounts to running 2,404,808,340 regressions for each local projection specification selection and maximizing goodness-of-fit.[11] In the selected specification, we then include the monetary policy shock and two lags of the shock.

[10]These variables include log industrial production, the log of a commodity price index, the unemployment rate, the federal funds rate, the log S&P 500 index, and the log nominal broad U.S. dollar index. We also include the Greenbook forecasts of inflation.

[11]We varied this procedure in various ways and found it to give similar estimates for $\beta_{i,h}$ as long as at least a handful of control variables was allowed to be selected. Interestingly we found that including the USD exchange rate among the selected regressors tended to sharpen the estimates.

Standard errors. When we analyze IRFs, we compute HAC standard errors (Newey and West, 1987) for the estimator $\hat{\beta}_{i,h}$. We choose a bandwidth of $h+1$ as is common in the literature, see e.g. Ramey (2016).

2.3 Re-aggregation of IRFs using SUR

For a given level of disaggregation, suppose the aggregate PCEPI is defined as

$$P_t = \sum_i^N \omega_{i,t} p_{i,t}. \tag{2}$$

Note that in practice the PCEPI is not constructed as a simple weighted average of individual prices, but we use definition (2) for expositional purposes in this section and revisit it further below.

To study the response of the PCEPI to monetary policy shocks, we can run the specification in (1) using P_t instead of $p_{i,t}$. When doing so, we obtain the IRF of the aggregate price at horizon h as the coefficient on $\hat{\varepsilon}_t^m$, which we denote $\hat{\mathcal{B}}_h$.

Alternatively, we can run individual local projections for each price i and obtain the re-aggregated IRF estimate

$$\hat{\mathcal{B}}_h^{agg} = \sum_i^N \omega_{i,t} \hat{\beta}_{i,h}. \tag{3}$$

This is possible due to the linearity of the local projection and the linearity of the aggregation. In large samples, $\hat{\mathcal{B}}_h$ and $\hat{\mathcal{B}}_h^{agg}$ are identical.

The insight into the re-aggregation of individual IRFs allows us to construct counterfactual estimates. We can construct a hypothetical aggregate PCEPI response to a monetary policy shock, assuming different actual or hypothetical expenditure shares, instead of the true shares $\omega_{i,t}$. For example, we can use the weights for the year 2023 to obtain

$$\hat{\mathcal{B}}_h^{agg,2023} = \sum_i^N \omega_{i,2023} \hat{\beta}_{i,h}. \tag{4}$$

$\hat{\mathcal{B}}_h^{agg,2023}$ might be different from $\hat{\mathcal{B}}_h^{agg}$ in interesting and economically meaningful ways. It is of particular interest to carry out a re-aggregation using these latest expenditure shares. Comparing this response to the response of the actual PCEPI itself will be informative about whether changing expenditure shares might have accelerated or decelerated the response of the aggregate price level to a change in monetary policy.

Main econometric challenge and SUR approach. A key issue with the construction of the re-aggregated IRF estimator $\hat{\mathcal{B}}_h^{agg}$ is the construction of standard errors. When we run (1) for two different components i and j we would expect the estimates of $\beta_{i,h}$ and $\beta_{j,h}$, to be correlated. In almost any macroeconomic model with a cross-section of different goods, there is some form of co-dependence between their prices. Therefore, to correctly compute standard errors for $\hat{\mathcal{B}}_h^{agg}$ we need to obtain appropriate covariance estimates.

To do so, we define a SUR system for each horizon h. We first stack the observations in the time dimension, for each i and h:

$$\log \boldsymbol{p}_{i,h} = \alpha_{i,h} + \beta_{i,h}\hat{\boldsymbol{\varepsilon}}^m + \gamma_{i,h}\boldsymbol{X}_i + \boldsymbol{u}_{i,h}, \tag{5}$$

where bold symbols indicate vectors and matrices that are stacked in the t-dimension. Next, we further stack the N local projection equations on top of each other, and combine the control variables, to define the SUR system

$$\begin{bmatrix} \log \boldsymbol{p}_{1,h} \\ \vdots \\ \log \boldsymbol{p}_{N,h} \end{bmatrix} = \begin{bmatrix} \tilde{\boldsymbol{X}}_1 & 0 & \dots & 0 \\ 0 & \tilde{\boldsymbol{X}}_2 & \dots & 0 \\ \vdots & \vdots & \ddots & \vdots \\ 0 & 0 & \dots & \tilde{\boldsymbol{X}}_N \end{bmatrix} \begin{bmatrix} \boldsymbol{\Gamma}_{1,h} \\ \vdots \\ \boldsymbol{\Gamma}_{N,h} \end{bmatrix} + \begin{bmatrix} \boldsymbol{u}_{1,h} \\ \vdots \\ \boldsymbol{u}_{N,h} \end{bmatrix} \tag{6}$$

or, more compactly,

$$\log \boldsymbol{p}_h = \tilde{\boldsymbol{X}}\boldsymbol{\Gamma}_h + \boldsymbol{u}_h. \tag{7}$$

Each $\tilde{\boldsymbol{X}}_i$ collects a vector of ones, the monetary policy shock and its lags, the lag of the left hand side variable and the other control variables selected for price component i. Correspondingly, each $\boldsymbol{\Gamma}_{i,h}$ collects $\alpha_{i,h}, \beta_{i,h}$, $\gamma_{i,h}$ and $\delta_{i,h}$. In this system, we allow for dependence in the i-dimension, denote $\mathbb{E}[\boldsymbol{u}'_{i,h}\boldsymbol{u}_{j,h}] = \sigma_{ij,h}$, and define an $N \times N$ matrix $\boldsymbol{\Sigma}_h$ where the (i,j)-th element is $\sigma_{ij,h}$. The covariance matrix of the stacked residual of the local projection system $\boldsymbol{u}_h$ is $\boldsymbol{\Omega}_h \equiv \boldsymbol{\Sigma}_h \otimes \boldsymbol{I}_T$, where $\otimes$ is the Kronecker product and $\boldsymbol{I}_T$ an identity matrix of dimension T.

Estimation via feasible GLS. We proceed in two steps. First, we estimate the local projection for each price i at horizon h with OLS and retrieve N residual vectors $\hat{\boldsymbol{u}}_{i,h}$. We compute $\hat{\sigma}_{ij,h} = \frac{1}{T}\hat{\boldsymbol{u}}'_{i,h}\hat{\boldsymbol{u}}_{j,h}$ to construct the estimate of the covariance matrix $\hat{\boldsymbol{\Omega}}_h = \hat{\boldsymbol{\Sigma}}_h \otimes \boldsymbol{I}_T$. Second, we run FGLS to obtain

$$\hat{\boldsymbol{\Gamma}}_h^{FGLS} = \left(\tilde{\boldsymbol{X}}'(\hat{\boldsymbol{\Sigma}}_h^{-1} \otimes \boldsymbol{I}_T)\tilde{\boldsymbol{X}}\right)^{-1} \tilde{\boldsymbol{X}}'(\hat{\boldsymbol{\Sigma}}_h^{-1} \otimes \boldsymbol{I}_T) \log \boldsymbol{p}_h. \tag{8}$$

The IRFs at horizon h of each price to a monetary policy shock are the entries in the vector $\hat{\boldsymbol{\Gamma}}_h^{FGLS}$ that correspond to the position of the $\beta_{i,h}$ coefficient in the stacked system (7). The covariance matrix of $\hat{\boldsymbol{\Gamma}}_h^{FGLS}$ is

$$Var(\widehat{\hat{\boldsymbol{\Gamma}}_h^{FGLS}}|\tilde{\boldsymbol{X}}) = \hat{\sigma}^2_{FGLS} \left(\tilde{\boldsymbol{X}}'(\hat{\boldsymbol{\Sigma}}_h^{-1} \otimes \boldsymbol{I}_T)\tilde{\boldsymbol{X}}\right)^{-1} \tag{9}$$

with

$$\hat{\sigma}^2_{FGLS} = df^{-1}\left(\log \boldsymbol{p}_h - \tilde{\boldsymbol{X}}\hat{\boldsymbol{\Gamma}}_h^{FGLS}\right)'(\hat{\boldsymbol{\Sigma}}_h^{-1} \otimes \boldsymbol{I}_T)\left(\log \boldsymbol{p}_h - \tilde{\boldsymbol{X}}\hat{\boldsymbol{\Gamma}}_h^{FGLS}\right) \tag{10}$$

where df corresponds to the degrees of freedom.

Standard errors of re-aggregated IRFs. Now we can compute the standard error of the re-aggregated IRF $\hat{\mathcal{B}}_h^{agg}$, defined in (3), as

$$SE(\hat{\mathcal{B}}_h^{agg})^{SUR} = \sqrt{\sum_i^N \omega_i^2 \hat{\sigma}^2_{\hat{\beta}_{i,h}^{FGLS}} + \sum_i^N \sum_{j \neq i}^N \omega_i \omega_j \hat{\sigma}_{\hat{\beta}_{i,h}^{FGLS},\hat{\beta}_{j,h}^{FGLS}}}, \tag{11}$$

where $\hat{\sigma}^2_{\hat{\beta}_{i,h}^{FGLS}}$ and $\hat{\sigma}_{\hat{\beta}_{i,h}^{FGLS},\hat{\beta}_{j,h}^{FGLS}}$ denote the variance and covariance estimators of the IRFs. These correspond to entries of the $Var(\widehat{\hat{\boldsymbol{\Gamma}}_h^{FGLS}}|\tilde{\boldsymbol{X}})$ matrix. In a "naive" aggregation where the OLS estimates are used and treated as independent, we would have

$$SE(\hat{\mathcal{B}}_h^{agg})^{naive} = \sqrt{\sum_i^N \omega_i^2 \hat{\sigma}^2_{\hat{\beta}_{i,h}^{OLS}}}. \tag{12}$$

Since covariances between local projections estimates $\hat{\sigma}_{\hat{\beta}_{i,h}^{FGLS},\hat{\beta}_{j,h}^{FGLS}}$ can be either positive or negative, the difference between the naive standard error given by (12) and the correct one given by (11) cannot be signed.

To ensure that we draw inference for our re-aggregated IRF in the same way as for the individual IRFs, we additionally construct HAC standard errors in our FGLS system. This is possible by first computing the Cholesky factorization $\boldsymbol{\Omega}_h^{-1} = \boldsymbol{C}\boldsymbol{C}'$ and then setting up a regression of $\boldsymbol{C} \log \boldsymbol{p}_h$ on $\boldsymbol{C}\tilde{\boldsymbol{X}}$. We then estimate this system via the Generalized Method of Moments (GMM), by using Matlab's 'hac' command. As for the individual local projections, we choose the bandwidth $h + 1$.

2.4 Putting our econometric approach into perspective

Relation with panel local projections. Our SUR approach is different from the way panel local projection are often applied in the literature that studies microeconomic responses to macroeconomic shocks. In a typical version of such a panel local projection, we would assume that $\beta_{i,h}$ is the same across individual units of observations. By adding an additional interaction term, the coefficient might differ across a selected characteristic, such as firm leverage or distance to default as in Ottonello and Winberry (2020) or type of borrowing constraint as in Drechsel (2023). A recent econometric treatment of panel local projections is given by Almuzara and Sancibrián (2024). In our approach, each unit of observation has a different $\beta_{i,h}$, which in effect amounts to a panel local projection where we interact the main coefficient with a cross-sectional fixed effect. Our re-aggregation procedure allows us to then average the heterogeneity in the effects, to obtain an aggregate IRF. This procedure could be relevant for other applications in which disaggregated local projections are constructed and aggregation is desired, including local projections at the household, firm or bank level.

Relation with other GLS approaches to local projections. The FGLS estimation in our SUR procedure relates to other approaches to estimating local projections using FGLS. For example, Lusompa (2023) proposes FGLS as a way to account for serially correlated errors in individual local projections, as an alternative to HAC standard errors. Tanaka (2020) also stacks the local projections for an individual variable across horizons and treats them as a multivariate regression (SUR) system with correlated residuals. Both approaches are different from our SUR/GLS approach because they are still an approach to the local projection for one individual variable and not a cross-section of variables. Our focus is on drawing correct inference about aggregated IRFs, which makes the potential dependence across different prices crucial. It is possible to *additionally* stack our system of local projections in the horizon dimension, that is, to collect all $\log \boldsymbol{p}_h, h = 0, \ldots, H$ in one big vector and collect all control matrices $\tilde{\boldsymbol{X}}$ and parameter matrices $\boldsymbol{\Gamma}_h$ each in one big matrix. Estimating this "double-stacked" system with GLS is computationally challenging in our application, as it would involve inverting matrices of several million rows and columns. We only stack the system in the cross-sectional (price) dimension and additionally account for serially correlated errors in the local projection for each given price, by computing HAC standard errors with GMM, as discussed above.

3 Results for aggregate and disaggregate price indices

3.1 Aggregate PCEPI response

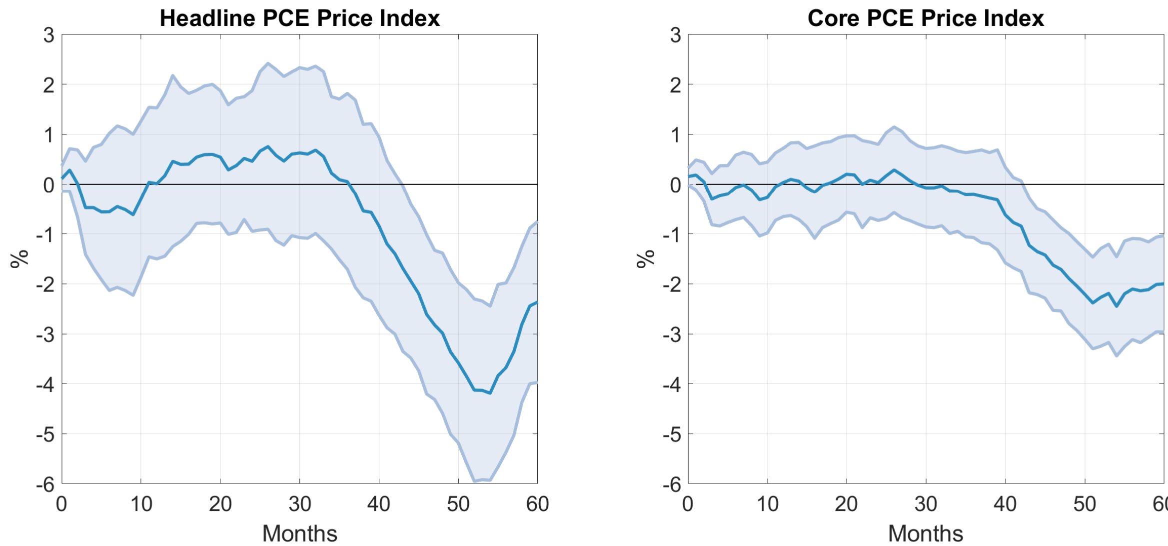
Figure 1 plots IRFs to a monetary policy contraction, reflected by an exogenous 100 basis point positive FFR shock. The left panel shows the headline PCEPI and the right panel the core PCEPI, which excludes food and energy prices. In each case, we plot the response of 100 times the log of the index. The solid line reflects the point estimate and the shaded areas represent 90% confidence bands based on HAC standard errors.

The IRF of the headline PCEPI displays a gradual decline, turning significantly negative at conventional levels only after 43 months. The peak reduction occurs after 54 months and our point estimate amounts to a roughly 4% lower price level after a 100 basis point monetary policy contraction. Economically, this is a relatively sizeable response, but it occurs after a long lag. It is also noteworthy that the point estimate implies even a slight increase in the PCEPI between years 1 and 3, but statistically it cannot be rejected that this response is equal to zero.

We estimate a very similar timing for the response of the core PCEPI. The magnitude of the response is smaller than for the total PCEPI, with a point estimate that implies a 2.5% price level reduction after a 100 basis point tightening shock. The IRF is estimated with greater precision than for the headline PCEPI. However, the long-lagged pattern is also visible for the core index.

The lagged patterns in aggregate price level responses shown in Figure 1 echo existing findings from the literature. For example, in Christiano, Eichenbaum, and Evans (1999), the aggregate price level does not fall to a statistically significant extent

Figure 1: IRFS TO MONETARY POLICY TIGHTENING: AGGREGATE PRICE INDICES



Notes. IRFs are estimated with local projections using the identified monetary policy shocks of Aruoba and Drechsel (2023). The shock is normalized to a 100 basis point increase. Shaded areas represent 90% confidence bands based on HAC standard errors. The core PCEPI excludes food and energy prices.

for 4 years after an FFR increase. The GDP deflator IRF we estimate in Aruoba and Drechsel (2023) is equally sluggish. In the Online Appendix, we provide a table with a comprehensive analysis of corresponding price level responses to monetary policy shocks in the literature. That analysis makes clear that our lagged dynamics we document are on the larger end but not out of the ordinary, given what the previous literature has found. Interestingly, there is some disagreement in the results between SVAR and narrative approaches on the one hand, and high-frequency approaches on the other hand. The latter approaches tend to find shorter horizon at which the effects first turn statistically significant. When it comes to the lag of the peak response, however, there is greater alignment between the findings with different methodologies to identify monetary policy shocks and estimate their effects.

What stands out about our estimates, also relative to other studies in the literature, is that it is not only generally gradual but that it is flat for several years. Our subsequent analysis unpacks the cross sectional drivers of this pattern. It will reveal that underlying our estimated aggregate IRFs, we see strong heterogeneity in the responses of more disaggregated price indices, especially early on.

3.2 Responses of PCEPI subcomponents

We now analyze IRFs of disaggregated price indices, moving from rougher to finer levels of disaggregation. We skip the basic distinction between goods and services and begin with the second level of disaggregation, which separates durable goods, nondurable goods and services. We move all the way to the fifth level of disaggregation with 136 price categories.

Disaggregation level 2. Figure 2 plots the IRFs of prices of durable goods, nondurable goods and services to a monetary policy tightening. The figure also shows the response of prices of consumption of nonprofit institutions serving households (NPISHs), the fourth price component at this level of disaggregation. The unit is again 100(log-level) or percent. In each panel, we also superimpose the point estimate of the aggregate headline PCEPI IRF from the left panel in Figure 1, as a dashed line.

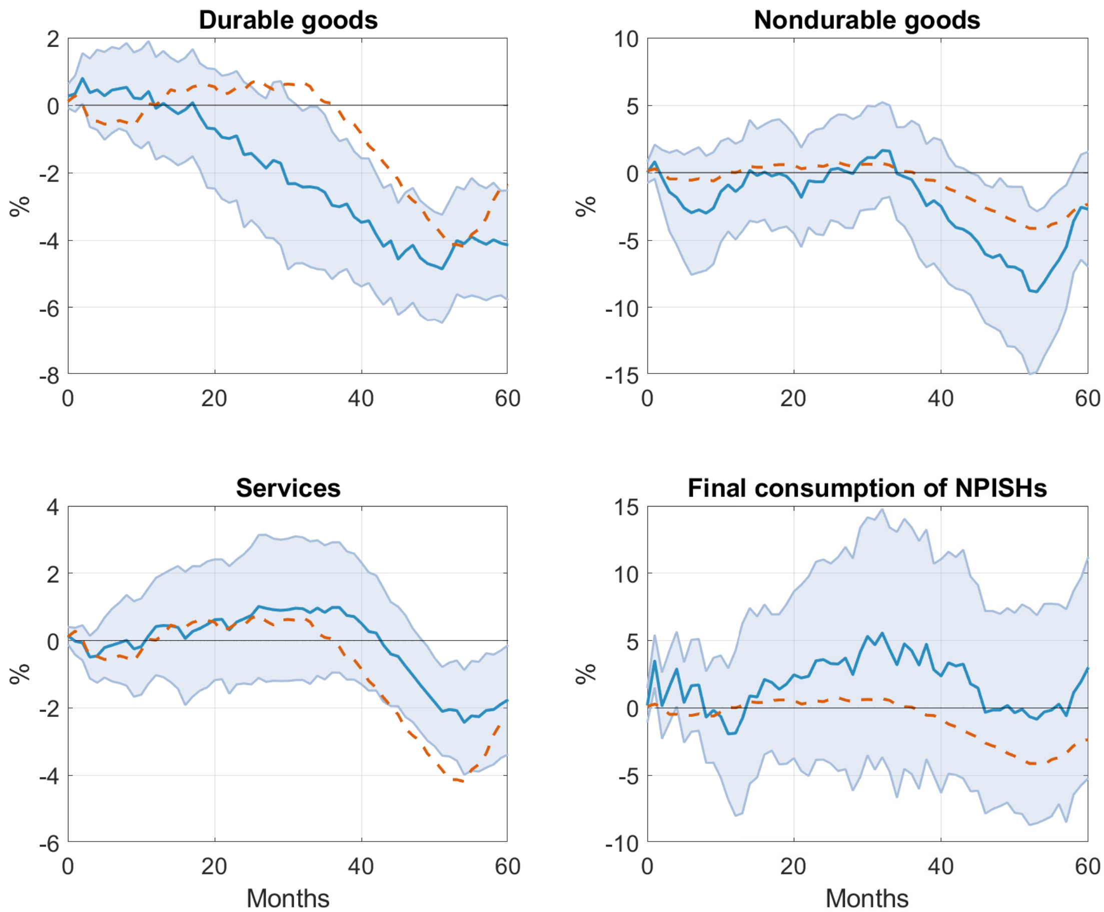
Comparing the different panels of the figure makes clear that already at this relatively rough level of disaggregation, there is meaningful heterogeneity in the dynamics of prices following a monetary policy tightening. Prices of durable goods decline at the fastest pace, with a statistically significant response after 2.5 years. They show a peak reduction of around 5% after roughly 4 years. The fact that the durable goods sector is more interest-rate sensitive is a well-known fact in the literature. See e.g. Erceg and Levin (2006); McKay and Wieland (2021).

Nondurable goods prices take much longer to decline. The point estimate is more sizable than for durable goods, at around 8% but also less precisely estimated. The IRF of services prices looks most similar to the aggregate PCEPI response, but is slightly slower and smaller in magnitude. The NPISH response is entirely insignificant. In the subsequent analysis, we exclude NPISH categories, because they carry a negligible weight on the aggregate PCEPI, accounting for only 2.2% of expenditures.

Disaggregation level 3. Figure 3 plots the IRFs of prices in the third level of disaggregation, which amounts to 17 price subcomponents (excluding two NPISH categories). We again show the point estimate 90% HAC bands and superimpose the aggregate PCEPI response as a dashed line.

The figure reveals quite drastic differences in the price responses to a monetary

Figure 2: IRFS TO MONETARY POLICY TIGHTENING: DISAGGREGATION LEVEL 2

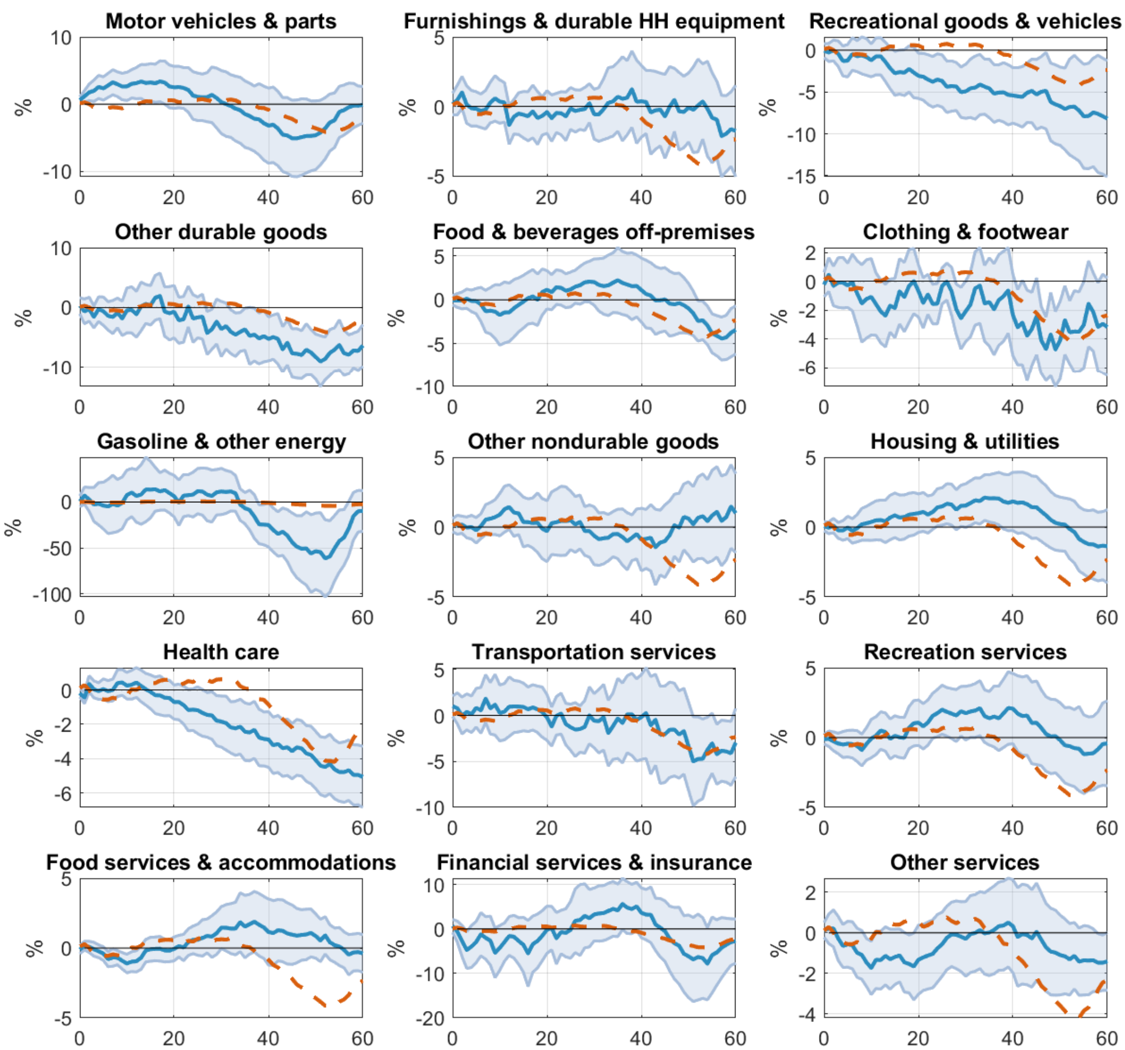


Notes. IRFs estimated with local projections using the identified monetary policy shocks of Aruoba and Drechsel (2023). The shock is normalized to a 100 basis point increase. Shaded areas represent 90% confidence bands based on HAC standard errors. The dashed line in each panel corresponds to the point estimate of the IRF of the aggregate headline PCEPI. NPISHs are nonprofit institutions serving households.

policy tightening. After a monetary policy contraction, some important price categories respond negatively after a long delay or even a positive initial response, while others fall more rapidly. Especially at short horizons there are differences across categories, with negative, positive and many flat responses. At longer horizons, the responses of the different price categories start getting more into sync, with many of them becoming significantly negative.

In particular, we find that important categories such as gasoline, transportation services and motor vehicles respond negatively after a long delay. For some

Figure 3: IRFS TO MONETARY POLICY TIGHTENING: DISAGGREGATION LEVEL 3



Notes. IRFs estimated with local projections using the identified monetary policy shocks of Aruoba and Drechsel (2023). The shock is normalized to a 100 basis point increase. Shaded areas represent 90% confidence bands based on HAC standard errors. The dashed line in each panel corresponds to the point estimate of the IRF of the aggregate headline PCEPI. We exclude categories related to nonprofit institutions serving households, which carry a negligible weight on the aggregate.

components, the initial response to an interest rate increase is even positive.[12] For the motor vehicle category, it turns out that the positive response is driven by the subcategory of used motor vehicles (not separately shown in Figure 3). One potential explanation might be that new vehicle purchases are so interest rate sensitive that substitution from new to used vehicles drives up the price of used vehicles.[13]

Other categories, such as clothing and footwear or recreational goods, fall more rapidly after a contractionary shock. In general, several of the durable goods categories tend to respond more swiftly, which links back to the discussion of the responses at disaggregation level 2. Several categories show responses that are not distinguishable from zero over all horizons.

The differences in magnitude across the variables are also substantial. For example, the response of gasoline and other energy products amounts to a reduction of almost 50% in the price level. The point estimates of other variables are also in the double digits of percent changes. In the Online Appendix, we show a version of Figure 3 in which we divide each IRF by the historical standard deviation of the respective (log) price series. This version of the IRFs makes clear that the responses are not as large when viewed in light of the historical standard deviation of a given price series. For example, in terms of standard deviations, the peak reduction in the price of gasoline and other energy products is between 0.1 and 0.2 standard deviation, relative to around 50% in levels. These numbers reflect that this category is just generally extremely volatile.

Disaggregation level 5. We skip disaggregation level 4, which amounts to 70 price components, and go directly to the finest disaggregation level considered by our analysis. This level consists of 136 different prices.[14] As plotting individual IRFs

[12] For some categories, we can tie back the positive responses to energy. For example, the price index for housing and utilities shows a positive (though insignificant) response for quite some time. We found that this is largely driven by the utilities subcategory, in particular electricity.

[13] For research on macroeconomic dynamics with different qualities of durable consumption goods, see Gavazza and Lanteri (2021).

[14] At disaggregation level 5, the set of price components starts become unbalanced, with some categories entering or dropping out over our the sample period. We construct a balanced version of level 5 by taking level 4 and replacing all items for which data is available for all level 5 from 1959M1 onwards. There are two reasons why level 5 items may not be available. Either the level 4 item is simply not subdivided into further items (level 4 is the first level with such ”terminal” items, such as “Religious organizations' services to household”), or at least one sub item only entered the PCEPI after 1959M1, for example “Video and audio streaming and rental” starts in 1982M1.

becomes visually unappealing, we summarize the insights from our analysis of IRFs at this disaggregation level by means of different types of figures. The Online Appendix includes the full set of individual IRFs.

At disaggregation level 5, we find that there are around 13% of price IRFs to monetary policy contractions for which the response is never significant in any direction. Around 17% of the responses turn positive at least once but never negative. That is, 40 IRFs at this level of disaggregation (around 30%) are never significantly negative. Also, out of the 136 series at level 5, exactly half are significantly positive at least once.

Figure 4, Panel (a) plots all disaggregation level-5 IRFs together with their mean and the aggregate response PCEPI response, but focuses only on those segments of the IRFs that are statistically significant. The plot shows that some price components are persistently and significantly positive and some are negative, even at quite large horizons. Panel (b) shows the fraction of price series that show a significant positive or negative response across horizons. At any given horizon, over 50% of series show an insignificant response. Early on, the shares of positive and negative responses are roughly the same, leading to the flat response and then eventually as enough series show a negative response, the overall PCEPI response goes negative.

Perhaps the most central insight of our analysis of price subcomponents is that the reason why the headline and core response is flat and fall after 4 years is *not* because all prices are unchanged for 4 years. On the contrary, many of them change but both positive responses and different turning points make it hard to get a clean negative response in the aggregate until enough of the series start falling. It is only at horizons of several years that the price decline after a monetary policy tightening is broad-based across many price categories.

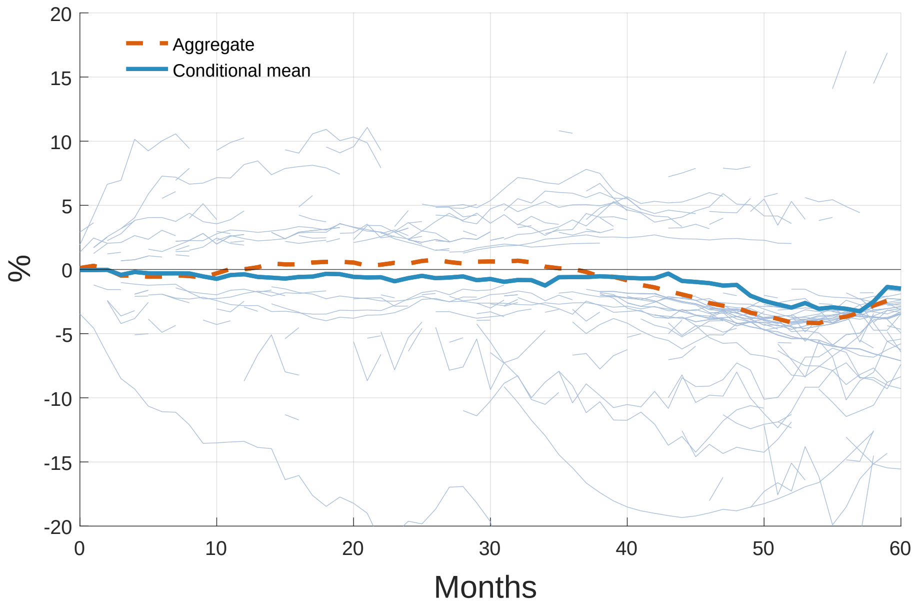
3.3 Responses of PCEPI contributions

In equation (2), we made the simplification that the aggregate index is a weighted sum of individual prices. However, the BEA's PCEPI is constructed as a chain-linked Fisher index. This means that the PCEPI is the geometric average of two distinct fixed-basket measures of the price level, the Laspeyres and Paasche indices. Thus, it is a nonlinear combination of all quantities and prices from consecutive periods. Consequently, the PCEPI cannot exactly be decomposed additively.

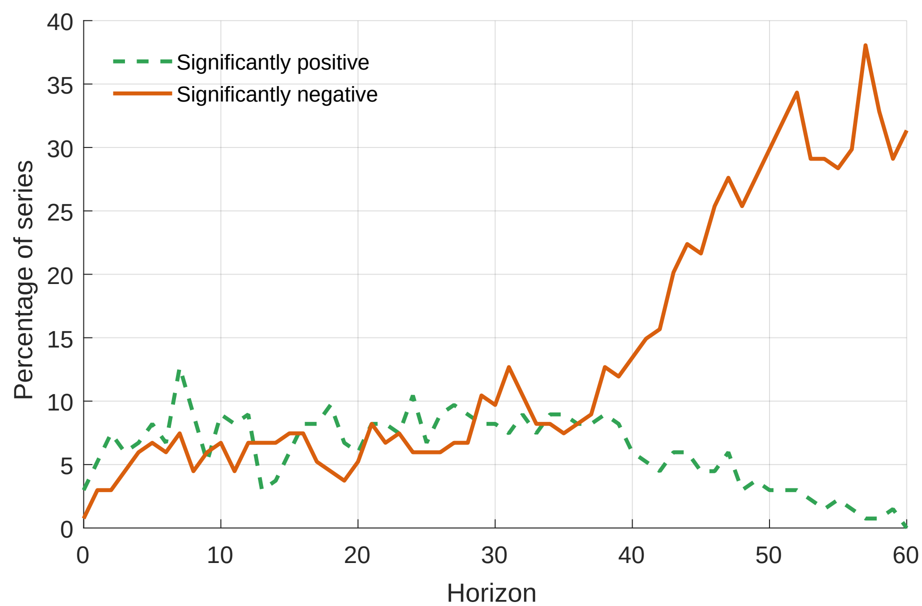
In addition to disaggregated price indices, the BEA releases data on the

Figure 4: INSPECTING SIGNIFICANTLY NEGATIVE RESPONSES AT LEVEL 5

(a) Significant segments of IRFs



(b) Fraction of significantly positive/negative IRFs



Notes: Panel (a) plots those segments of disaggregation level-5 IRFs that show a significant across horizons (some outliers have been removed). Panel (b) shows the fraction of level-5 IRFs that show a significant positive or negative response across horizons.

contribution of each subcomponent to PCEPI inflation, at different horizons. We denote this as $con^q_{i,t}$. Formally, PCEPI inflation over q months can be written as the sum of contributions

$$\Delta^q P_t = \sum_i^N con^q_{i,t}, \tag{13}$$

where $con^q_{i,t}$ is measured by the BEA for each price subcomponent i and for different q. Δ^q denotes the log-difference between $t+q$ and t.[15] Since the $con^q_{i,t}$ terms are contributions to the growth rate of the price level, we can cumulate them through time. For each subcomponent, this cumulated index tracks the net contributions of the component to PCEPI inflation across time. Thus, it is not only tracking the item's price but also the item's relative weight in the PCEPI. We denote this *contribution level* with $m^q_{i,t}$. It can be recursively defined as $con^q_{i,t} = \Delta^q m^q_{i,t}$, where the first observation is normalized to 100 for each subcomponent i. We focus on one-month ahead inflation ($q = 1$) and drop the q superscript from now on.

It is insightful to construct IRFs of the contribution levels to a monetary policy shock. We can do so with the same setup as in (1), but using $m_{i,t+h}$ instead of $p_{i,t+h}$ on the left hand side. The estimates of these 'contribution IRFs' now *exactly* sum up to the IRF of the aggregate PCEPI. Consequently, one would only estimate a large response when a combination of three factors occurs: (i) a large response in the price series, (ii) a large increase in the weight of the price series, or (iii) a great initial weight in the PCEPI.

Figure 5 shows the contribution IRFs at disaggregation level 4. In separate panels, we plot the IRFs for the 11 price subcomponents with the strongest contribution to the aggregate PCEPI, in descending order. We also show as a separate IRF the sum of all remaining contribution IRFs in one panel (on the bottom right). By construction, all IRFs in the figure add up to the total PCEPI IRF, which we superimpose in each panel for comparison.

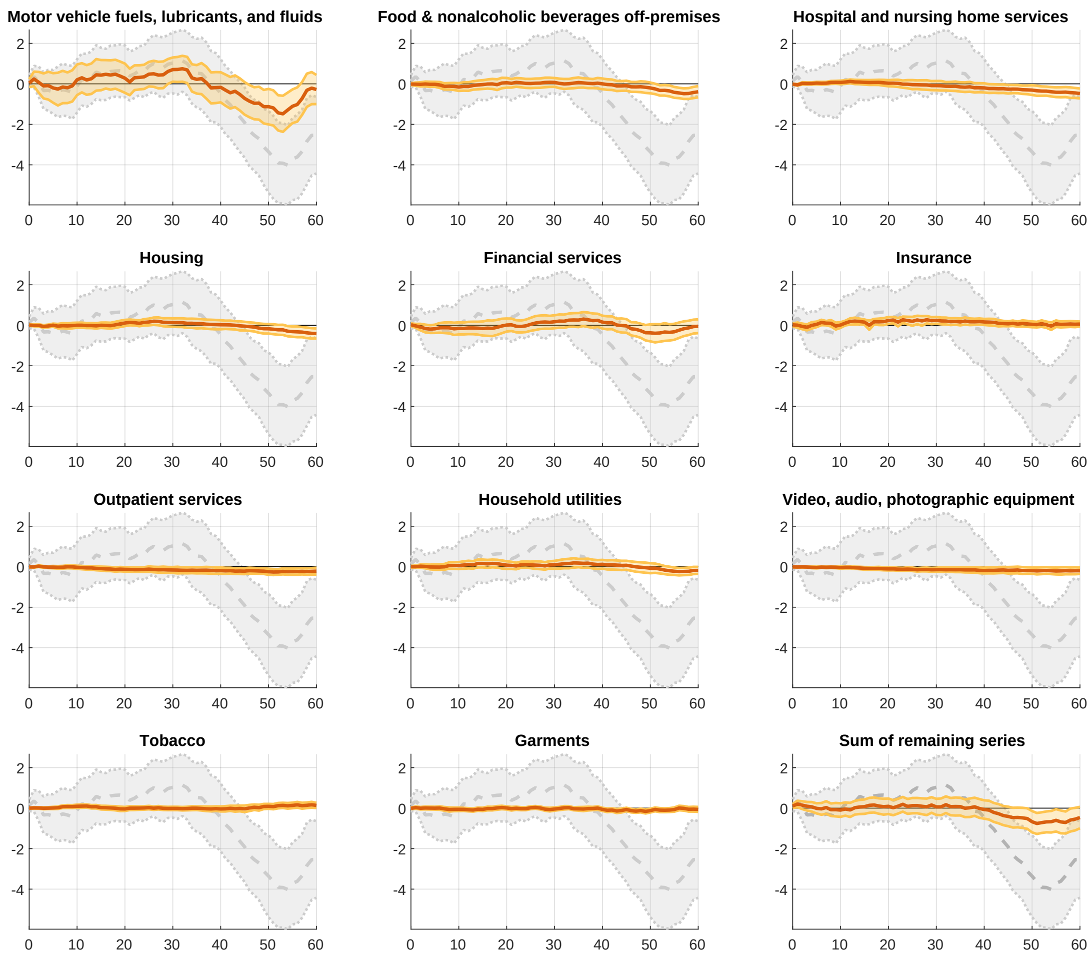
The figure reveals several insights. First, there is a lot of heterogeneity in

[15] For each price series i, we compute the contribution to PCEPI inflation between periods t and $t+q$ using the additive disaggregation proposed by Reinsdorf et al. (2002):

$$con^q_{i_t} = \frac{q_{it} + q_{it+q}(P_F/Q_F)}{\mathbf{p}'_t\mathbf{q}_t + (\mathbf{p}'_t\mathbf{q}_t)P_F}(p_{it+q} - p_{it}),$$

where p_{it}, q_{it} are component i's price and quantity in period t, bold letters represent vectors of prices or quantities, and P_F and Q_F are the price and quantity Fisher indices, respectively. The Fisher indices are $P_F = \sqrt{(\mathbf{p}'_{t+q}\mathbf{q}_t/\mathbf{p}'_t\mathbf{q}_t)(\mathbf{p}'_{t+q}\mathbf{q}_{t+q}/\mathbf{p}'_t\mathbf{q}_{t+h})}$ and $Q_F = \sqrt{(\mathbf{p}'_t\mathbf{q}_{t+q}/\mathbf{p}'_t\mathbf{q}_t)(\mathbf{p}'_{t+q}\mathbf{q}_{t+q}/\mathbf{p}'_{t+q}\mathbf{q}_t)}$.

Figure 5: IRFS TO MONETARY POLICY TIGHTENING: CONTRIBUTION SERIES



Notes. IRFs of contribution series (computation described in the text), estimated with local projections using the identified monetary policy shocks of Aruoba and Drechsel (2023). The shock is normalized to a 100 basis point increase. Shaded areas represent 90% confidence bands based on HAC standard errors. The dashed line in each panel corresponds to the point estimate of the IRF of the aggregate headline PCEPI.

the responses. Second, there are some positive price responses to a monetary tightening. The two insights confirm the results in the previous subsection. Third, a few components have a disproportionately large effect on the aggregate response. In fact, almost all contribution IRFs are quite flat throughout and almost all are entirely flat for the first few years. The strongest contribution comes from motor vehicle fuels, lubricants and fluids, which is a subcategory of gasoline and other energy goods. Other categories with strong contributions are food and nonalcoholic beverages off-premises and hospitals and nursing home services. Several IRFs do show a significantly negative sign after around 40 months. This is also the case for the sum of the remaining categories.

In the Online Appendix, we repeat the analysis in Figure 5 also for core instead of headline inflation. Similar insights emerge from that analysis. This is particularly noteworthy because core inflation excludes energy, of which motor vehicle fuels, lubricants and fluids is a subcategory. This makes clear that in terms of timing headline and PCEPI dynamics are not that different, as shown by Figure 1.

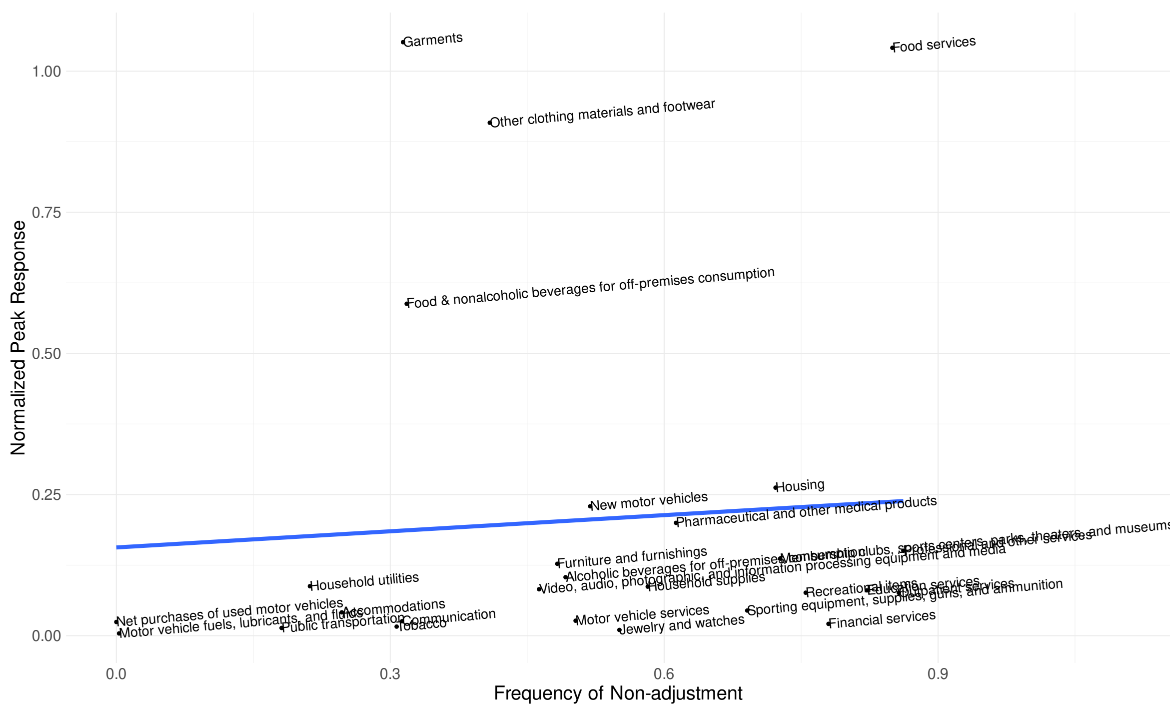
The contribution analysis shows that it is relevant to construct IRFs for both the level response of individual prices, as done in the previous subsection, as well as the cumulated contribution of each price to the total PCEPI. The combination of these two approaches allows us to paint a rich picture of the heterogeneity in the responses of different prices *and* the contribution of those responses to aggregate inflation dynamics.

3.4 Interpreting our cross-sectional findings

We find that a monetary policy tightening triggers both positive, negative and many flat price responses at short horizons and a broad-based decline in prices at long horizons. While there is no clear consensus on the responses of PCEPI subcomponents to monetary policy shocks in the existing literature, and this is in fact part of the motivation for our analysis, there are some previous empirical results that point in the same direction. The closest finding is in Boivin et al. (2009), who use a FAVAR approach. See in particular the top right panel in their Figure 3. These authors conclude that "a striking feature is that most indices respond very little for several months following the shock, and start falling only later." The results in Balke and Wynne (2007) based on PPI data also look similar to ours in that there first is a long delay and then a negative response in the aggregate price level.

Which theories of price adjustment might best explain the findings represented by our subcomponent IRFs? In what follows, we reason through some basic theories of price adjustment. While the set of theories we consider might not be exhaustive, we think this discussion helps to interpret our results theoretically. First, Calvo (1983) pricing cannot generate IRFs to monetary policy shocks that are shaped like the ones we estimate. In a Calvo model, there is a direct negative relationship between the peak response of a price to a monetary policy shock and the main

Figure 6: LAGS IN IRF PEAK RESPONSE VS. EMPIRICAL ESTIMATES OF PRICE STICKINESS



Notes: Scatter plot between the number of months at which the peak response of a given price occurs in our IRFs, normalized by the standard deviation of the respective price, (y axis) and price adjustment frequency estimates across PCEPI categories of Carvalho, Lee, and Park (2021).

Calvo parameter, which captures the probability that a firm cannot adjust its price. We can verify empirically whether our IRFs exhibit such a relation with empirical estimates of price adjustment. Figure 6 correlates the peak response of a given price in our IRFs with the price adjustment frequency estimates across PCEPI categories of Carvalho, Lee, and Park (2021).[16] We normalize the peak response by each series' historical standard deviation. The figure shows that there is, if anything, a weakly positive relationship between our peak response and the time it takes, unconditionally, for prices to adjust. A similar finding is presented in Luo and Villar (2023) (see their Figure 5a). Richer DSGE models with Calvo adjustment frictions (Smets and Wouters, 2007) or multi-sector models with heterogeneity in Calvo price stickiness (Pasten et al., 2020) also cannot explain our results.

[16] In the Calvo framework, peak response and impact response coincide. So we can compare the Calvo model to multiple objects in the data. We choose the peak of our IRFs as the data analogue.

Second, our IRFs are not consistent with menu cost models in the tradition of Golosov and Lucas (2007). In the standard menu cost model, as the menu cost increases and thus the frequency of price changes falls, the response of inflation to unanticipated increases in nominal money supply monotonically decreases. There is no mechanism to make the response of firm-level prices switch signs. A firm either changes its price the same direction as the change in nominal money supply, because it is willing to pay the menu cost, or it does not change prices at all.[17]

The third set of theories to consider are those with information frictions. The sticky information model of Mankiw and Reis (2002) do not generate IRFs with an initial flat region and then a delay later on or positive responses of some producers. See for example the IRFs of inflation to a monetary policy shock in Reis (2009), which respond instantaneously. A flat region in the IRF is also not present in the comparison of sticky and noisy information models in Woodford (2001). Mackowiak and Wiederholt (2009) focus on rational inattention. In their model, IRFs to different shocks can have a large delay, but they are hump-shaped instead of first being flat and then showing a strong response after several years, like our estimated IRFs.[18] The sticky expectations model of Auclert et al. (2020) features an inflation response that is quite gradual, but also does not feature a flat part early on. Interestingly, the empirically estimated price level IRF in Auclert et al. (2020) based on Romer and Romer (2004) shocks is insignificant for several years, similar to ours.

We speculate that a model that can generate the patterns we document across subcomponents might have at least one of two features. First, there could be a cost channel through which higher nominal rates act like an increase in marginal costs to some sectors, as modeled in a one-sector economy by Ravenna and Walsh (2006). For example, a monetary policy tightening could constrain supply of firms with financial constraints that tighten when nominal interest rates rise. If there is heterogeneity in such a cost channel across sectors, monetary policy shocks could act as demand shocks to some sectors but supply shocks to other sectors, with the aggregate demand effect eventually dominating across sectors at long horizons. Second, there could be a strong demand substitution channel between different goods and services. If higher interest rates lower demand for one good

[17] Gautier and Le Bihan (2022) build a multi-sector menu cost model in which there is stronger money non-neutrality (which means inflation responds less to monetary policy shocks). But these authors do not report individual price responses.

[18] Further models of monetary policy with information frictions that do not generate IRFs similar to our estimates are Adam (2007) and Melosi (2016).

and consumers instead substitute into an alternative good, then the price of the alternative good might rise, or stay stable, in the short run. However, as total demand decreases, all prices fall eventually as substitution forces fade away and the aggregate demand force dominates. We provided such an effects as a tentative explanation for the difference in the new and used vehicle responses further above.

These theoretical mechanisms might arise in particular in network economies. In their analysis of PPI series, Balke and Wynne (2007) find that there are more initially positive responses in final goods than in intermediate goods, and more in intermediate goods than in crude good prices. In other words, the more downstream a product is, the more likely is an initially positive response. They speculate that an input-output structure with heterogeneous financial constraints could explain their findings because, in such a model, a monetary tightening would act as a cost-push shock for some (financially constrained) sectors, while in other sectors the traditional demand shock would outweigh. The model of Luo and Villar (2023) also generates sector specific cumulative price responses that range from negative to positive.[19] This mechanism connects to the idea of "Keynesian supply shocks" in multi-sector economies developed by Guerrieri et al. (2022).

4 Results from re-aggregation experiments

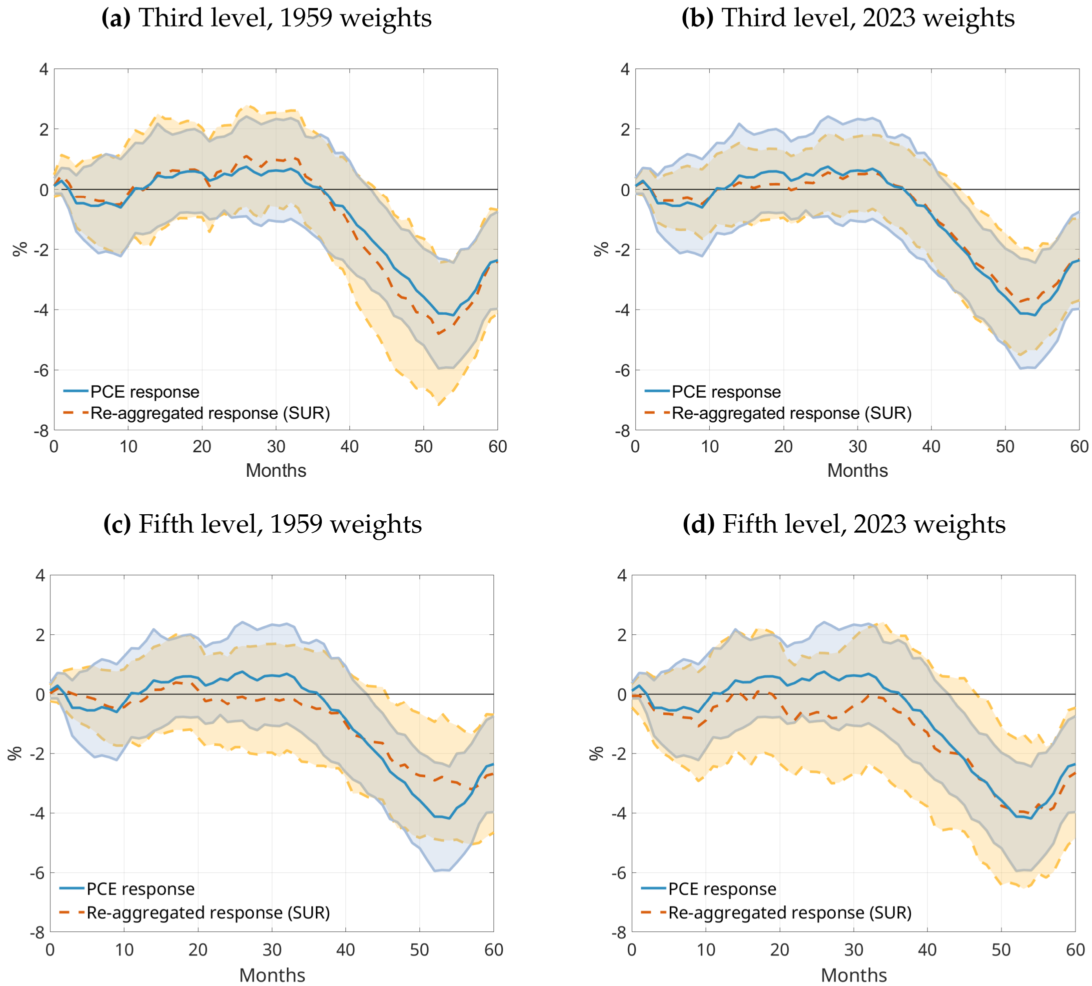
This section turns to our re-aggregation experiments. As explained in Section 2.3, we take individual IRFs at a given level of disaggregation and then re-build an aggregate price level IRF using actual and hypothetical expenditure weights. We use a SUR approach to correctly aggregate standard errors such that they can account for cross-sectional dependence.[20]

Headline PCEPI estimates with weights from different years. Figure 7 shows different IRFs that are re-aggregated to the headline PCEPI IRF, together with the IRF estimated the actual aggregate headline PCEPI. We consider re-aggregation of

[19] A network structure itself would not be sufficient without the two effects described in the previous paragraph. For example, in the model of Afrouzi and Bhattarai (2023) all inflation responses seem to move in the same direction. Interestingly, the network structure does introduce persistence.

[20] As explained in previous sections, the PCEPI is not exactly an expenditure weighted sum. Therefore, there is some approximation error in all of our re-aggregated responses. We verified that this approximation error is small enough to not obscure our graphical comparisons below.

Figure 7: RE-AGGREGATION EXPERIMENTS FOR DIFFERENT YEARS: HEADLINE PCEPI



Notes: IRFs of headline PCEPI to identified monetary policy shocks. Each panel contains the IRF based on re-aggregation procedure, using different levels of disaggregation and different expenditure shares (dashed lines). Each panel also shows the re-aggregated IRF as well the IRF of aggregate headline PCEPI as the solid lines. The shaded areas represent 90% significance bands based on HAC standard errors, and in the case of the re-aggregation accounting for cross-sectional dependence.

the level-3 IRFs and level-5 IRFs and in each case we use both 1959 expenditure weights and 2023 expenditure weights.

The SUR-based re-aggregation of our individual IRFs implies that, independent of whether 1959 or 2023 expenditure shares are used to re-aggregate, the price level falls with a similar timing than estimated with the aggregate series itself. This is visible when comparing panel (a) with (b) and comparing panel (c) with (d). The magnitude of the reduction is also similar. This finding implies that changing expenditure shares through time, e.g. because of structural change, have not accelerated the response of the PCEPI to monetary policy.

In the Online Appendix, we also provide a graphical analysis that uses the weights for every single year from 1959 to 2023, separately for different horizons. PCE shares are somewhat stale, that is, computed with a significant lag themselves, so they are likely not suitable for a year-by-year comparison. However, considering longer-term trends over a period of almost 80 years makes clear that they do not exhibit enough change to alter the response of the re-aggregated PCEPI to monetary policy shocks.

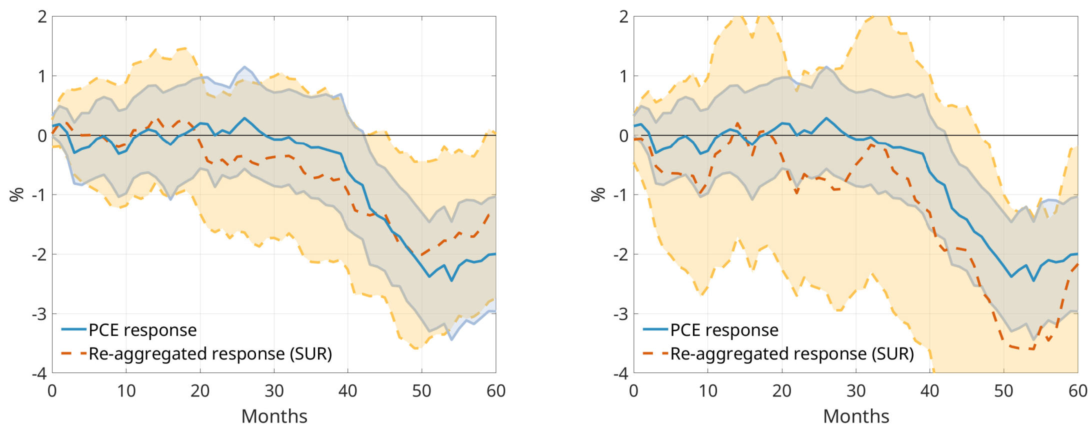
Core PCEPI estimates with weights from different years. Figure 8 repeats the analysis of Figure 7 but focuses on core PCEPI instead of headline PCEPI, re-aggregating the fifth disaggregation level. For core PCEPI, we find somewhat larger difference between the actual and the re-aggregated response. What is also different from the headline PCEPI picture is that the re-aggregated response becomes noisier. Broadly speaking, the conclusion that changes in expenditure shares have not accelerated the response of inflation to monetary policy, remains intact.

How have expenditure weights changes through time? We further interpret our re-aggregation result against the backdrop of the most important changes in consumer behavior. Figure 9 plots the expenditure shares corresponding to disaggregation level 3 from 1959 to 2023. It is evident that expenditure shares are relatively stable through time. The most market changes in expenditure shares that have happened over the last decades are a decrease in the share for food and beverages (-12 percentage points) and an increase for health care (+11 percentage points).

Both categories respond to monetary policy with a similarly long lag. What we cannot rule out with our methodology and data is that price stickiness across all or important categories has declined, which could accelerate the response. However, health care services are among the most sticky and least cyclically sensitive price categories (Stock and Watson, 2020; Carvalho, Lee, and Park, 2021). Note that health care services are also a category for which price measurement is notoriously difficult and imprecise.

Figure 8: RE-AGGREGATION EXPERIMENTS FOR DIFFERENT YEARS: CORE PCEPI

(a) Fifth level, 1959 weights | **(b)** Fifth level, 2023 weights

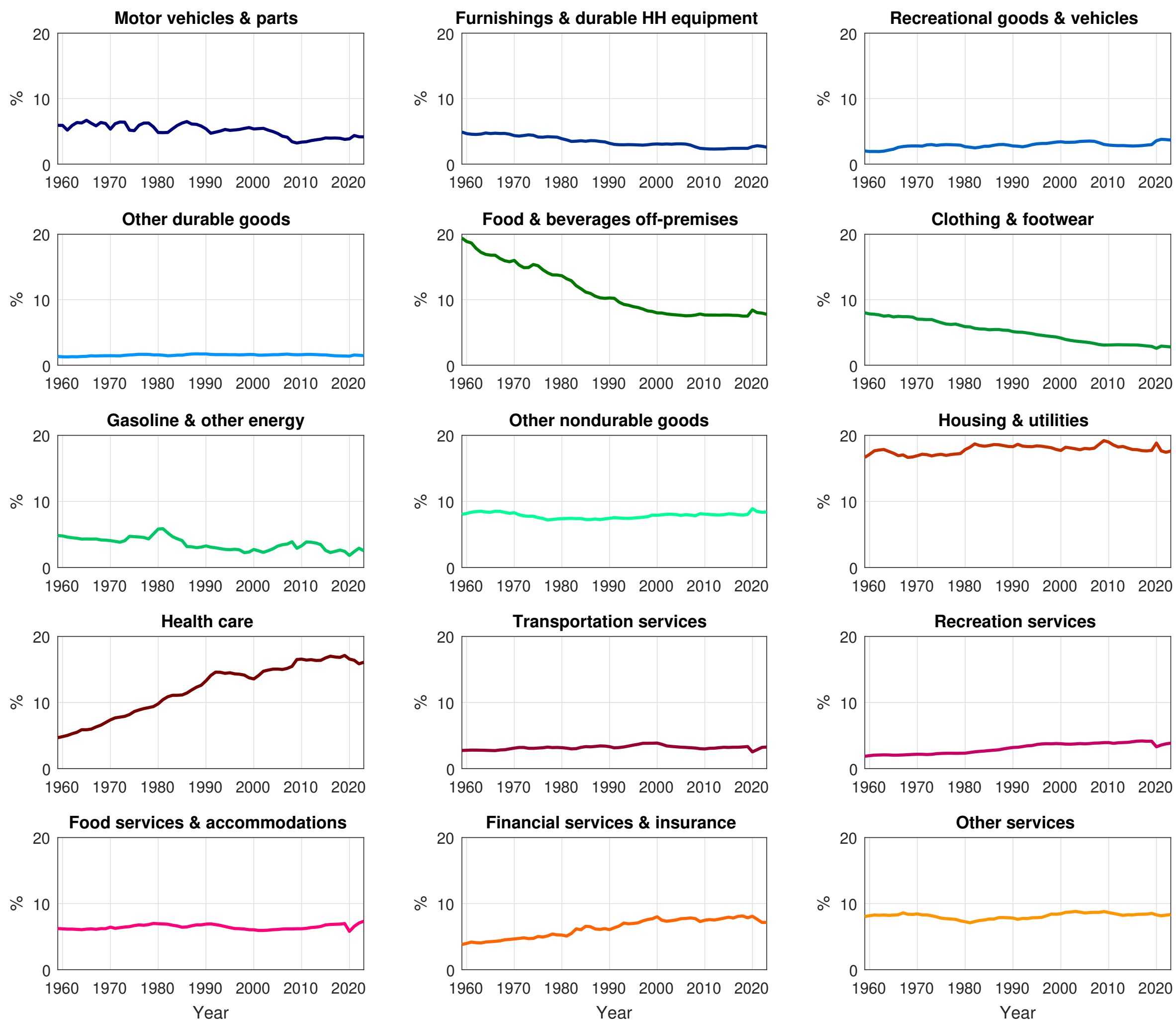


Notes: IRFs of core PCEPI to identified monetary policy shocks. Both panels contain the IRF based on re-aggregation procedure, using the fifth levels of disaggregation and different expenditure shares (dashed lines). Both panels also show the re-aggregated IRF as well the IRF of aggregate headline PCEPI as the solid lines. The shaded areas represent 90% significance bands based on HAC standard errors, and in the case of the re-aggregation accounting for cross-sectional dependence.

SUR-based aggregation vs. naive aggregation. Figure 10 examines in more detail the role of correctly adjusting the standard errors to account for cross-sectional dependence in the response of different price components to monetary policy shocks. For two selected cases, the re-aggregation of level-2 IRF with 2023 expenditure weights as well as the re-aggregation of level-5 IRFs with 2023 expenditure weights, we show different IRF estimates. The dashed lines represent the correct SUR based estimate in which the bands account for dependence between different prices. The dotted line represents a naive re-aggregation where the OLS estimates are used and no estimated covariance terms are taken into account. In other words, the estimates are treated as independent.

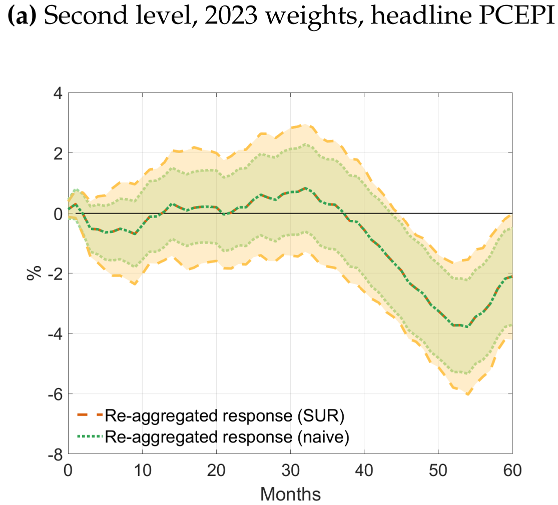
The figure shows that, while the difference in the standard errors between these two approaches cannot be signed (see discussion in Section 2.3), we find that the errors are generally larger when we take dependence into account. Our interpretation is that price movements are mostly positively related and therefore imply positive covariance terms. It is noteworthy that for the naive version and a confidence level slightly lower than the 90% level we use throughout, one would reject a zero response early on.

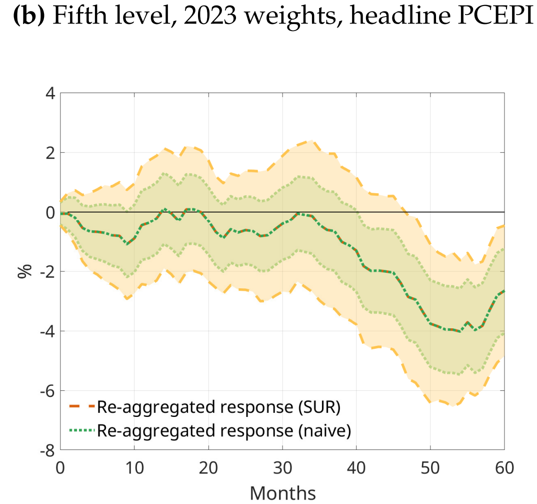
Figure 9: CONSUMPTION EXPENDITURE SHARES THROUGH TIME



Notes: Consumption expenditure shares through time. These correspond to expenditure categories from disaggregation level 3, for which IRFs are shown in Figure 3.

Figure 10: THE ROLE OF CORRECT INFERENCE IN AGGREGATING





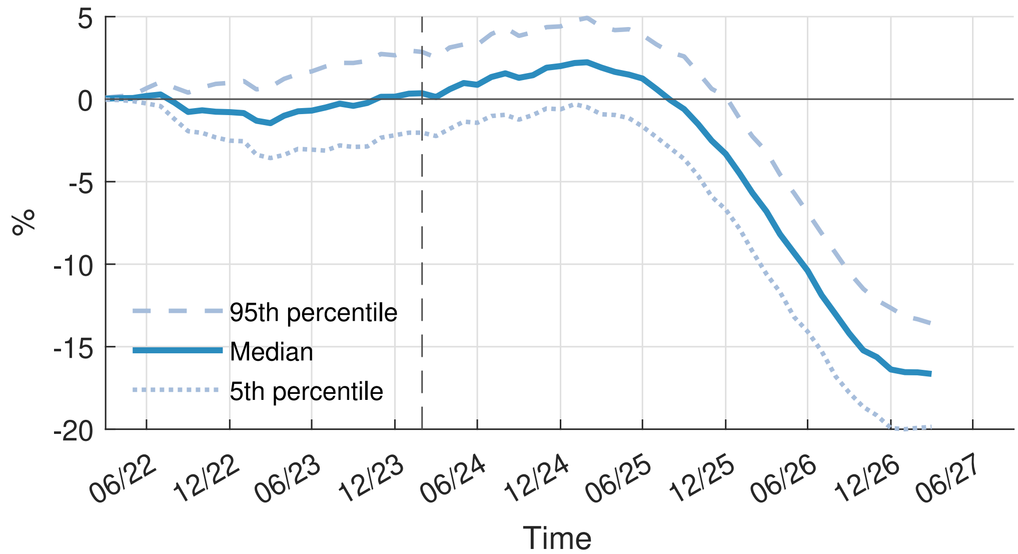
Notes: The dashed lines represent the correct SUR based estimate in which the bands account for dependence between different prices. The dotted line represents a naive re-aggregation where the OLS estimates are used and no estimated covariance terms are taken into account.

5 Broader discussion of our findings

Long and variable lags in price responses. Our results indicate that "long and variable lags" in the transmission of monetary policy, as described by Friedman (1960, 1961), are alive and well. The lags in the responses to monetary policy are *long* both for the aggregate price index and for individual price categories. While the attribute *variable* in Friedman's original insight referred to variability across time, we find large differences in the size and precise timing of the response across different prices. We provide evidence of variable lags in the cross-section of prices.

The evidence uncovered by our analysis suggests that the response of inflation to the Fed tightening in 2022-2023 might not yet be fully reflected in recent economic data. To illustrate this point visually, Figure 11 plots the cumulated PCEPI reduction that, according to our estimates, would result from the Fed's interest rate increases that occurred between March 2022 and July 2023. This calculation is intentionally somewhat provocative, as it conceptualizes the Fed's sequence of decisions as pure monetary policy shocks and assumes no other shocks occurred in the meantime. We do not intend this to be interpreted as a serious policy counterfactual, but as an illustration that puts our timing into the context of the sequence of policy changes that occurred in the last few years. The figure makes clear that the estimated lags in

Figure 11: CUMULATED PCEPI REDUCTION CORRESPONDING TO FED HIKES BEGINNING IN 2022



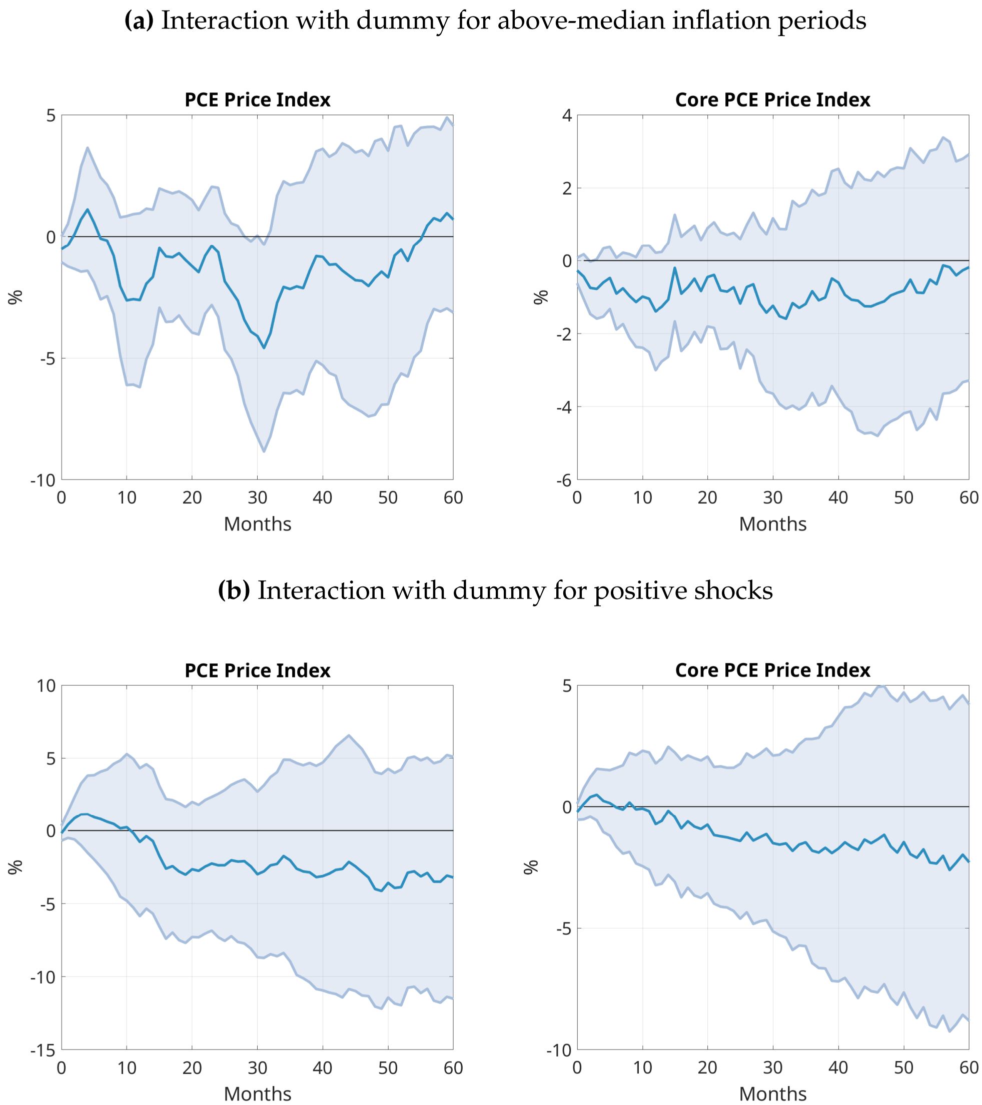
Notes: Cumulated estimated headline PCEPI reduction resulting from the Fed interest rate increases between March 2022 and July 2023, with 90% error bands. This calculation interprets the Fed's decisions as pure monetary policy shocks.

the reaction of prices to monetary policy are so long that, based on this provocative interpretation, *none* of the Fed's interest rate increases would be reflected in the inflation figures before the end of 2025.

What may be different now? The are several mechanisms that might render the lags in the response to monetary policy shorter, especially at the current juncture. In other words, there are various reasons why the analysis in Figure 11 is a limited interpretation of the price level effects of recent Fed policy. A monetary tightening that is very rapid, such as the one in 2022-23, might have a different effect on inflation, a form of nonlinearity in the effects. The effects of a policy tightening when inflation is already high might be stronger, a form of state-dependency. Or the effects might generally be stronger when monetary policy tightens rather than when it eases (see also Tenreyro and Thwaites (2016)).

Figure 12 explores both state-dependence and asymmetries in our estimates. Panel (a) shows the results from adding an interaction between the monetary policy shock and a dummy variable that is one in above-median inflation periods and zero

Figure 12: EXPLORING STATE-DEPENDENCE AND ASYMMETRIES IN THE EFFECTS



Notes: The IRFs in this figure represent the estimates of the coefficient on an additional interaction term that we add to the local projection for the headline and core PCEPI. In panel (a) we interact the monetary policy shock with a dummy variable that is one in above-median inflation periods and zero in below-median inflation periods. In panel (b) we interact the monetary policy shock with a dummy variable that is one when the monetary policy shock is positive and zero when it is negative.

in below-median inflation periods. We focus on both headline and core PCEPI on the left hand side of the local projection and plot the coefficient on the interaction term. This means that what appears in the plot is what is *added* to the IRFs in Figure 1 in high inflation periods. The point estimates for headline PCEPI indicate large negative effects. This means that in high inflation periods, the negative response to a monetary policy tightening might be quicker and stronger. However, the coefficient is estimated very imprecisely. We can only reject the null hypothesis that there is no state-dependence until around 30 months, a horizon that would still be considered a very long lag in the effects of monetary policy. The results for core PCEPI, shown as a separate plot, are insignificant across all horizons. Interestingly, a recent study by Canova and Perez Forero (2024) finds that in high inflation periods, the effects of monetary policy actually take longer than on average.

Panel (b) investigates asymmetries in our effects. It shows the results from adding an interaction between the monetary policy shock and a dummy variable that is one when the monetary policy shock is positive and zero when it is negative. Again, we focus on both headline and core PCEPI on the left hand side of the local projection and plot the coefficient on the interaction term. This means that what appears in the plot is what is *added* to the IRFs in Figure 1 when the shock reflects a tightening rather than an easing in monetary policy. While the point estimates are large and negative, we cannot reject the null hypothesis of no asymmetries, at any horizon and for both price level measures.

Nominal vs. real variables. Our analysis focuses primarily on prices. The analysis of contribution IRFs in Section 3.3 does take into account the changes in expenditure shares (i.e. quantity choices) in response to the monetary policy shock, but we did not separately analyze IRFs of any real economic variables in this study. In Aruoba and Drechsel (2023), we find that real activity responds much quicker than the price level to the same identified monetary shocks we employ here. The same is true for stock prices and credit spreads. Faster responses of real activity variable are also estimated by Buda et al. (2023) for very short horizons of only a few days. We leave a disaggregated analysis of quantities for PCEPI categories for future work. Such an analysis might connect our findings, at least loosely, to two separate lines of research.

First, we show that the effect of monetary policy on prices is very different in the cross-section. The link between inflation and real activity has also often been drawn in the cross-section, e.g. by bringing in cross-sectional data into Phillips curve estimation, see e.g. Hazell, Herreno, Nakamura, and Steinsson (2022) and Smith, Timmermann, and Wright (2023). Second, the fact that inflation picks up slowly and activity picks up quickly might be the reason that that motivates politicians to pressure central banks to ease policy prior to elections. The activity benefits of a pressure induced monetary easing might come first, while the price costs would materialize later. A related discussion is provided by Drechsel (2024).

6 Conclusion

This paper investigates how monetary policy affects PCEPI subcomponents. We find evidence of lags in the response of prices to monetary policy shocks that are *long* in the time dimension and *variable* in the cross-section of prices. The reason why aggregate price level measures remain flat for several years after a monetary policy tightening is not because all prices are unchanged initially. On the contrary, many prices change but both positive responses and different turning points make it hard to get a clean negative response in the aggregate until enough of the price series start falling. It is only at a horizon of several years that the decline is broad-based across most price categories. Using a re-aggregation procedure, in which we account for dependence in individual price estimates via a SUR approach, we can study hypothetical PCEPI responses to a monetary policy tightening using counterfactual expenditure shares. We find that changes in expenditure share have not accelerated the long-lagged response of inflation to monetary policy. Our findings have implications for the right calibration and time profile of monetary policy decisions, now and in the future.

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ONLINE APPENDIX TO

The long and variable lags of monetary policy: Evidence from disaggregated price indices

by S. Borağan Aruoba and Thomas Drechsel

Contents

A PCEPI categories at different levels of disaggregation

Table A.1: PCEPI CATEGORIES AT DIFFERENT LEVELS OF AGGREGATION

Level	Label	Code	5*
0	Personal consumption expenditures	PCE	—
1	Goods	PCE1	—
2	Durable goods	PCE11	—
3	*Motor vehicles and parts*	PCE111	—
4	New motor vehicles	PCE1111	—
5	New autos	PCE11111	Yes
5	New light trucks	PCE11112	Yes
4	Net purchases of used motor vehicles	PCE1112	—
5	Used autos	PCE11121	Yes
5	Used light trucks	PCE11122	Yes
4	Motor vehicle parts and accessories	PCE1113	—
5	Tires	PCE11131	Yes
5	Accessories and parts	PCE11132	Yes
3	*Furnishings and durable household equipment*	PCE112	—
4	Furniture and furnishings	PCE1121	—
5	Furniture	PCE11211	Yes
5	Clocks, lamps, lighting fixtures, and other household decorative items	PCE11212	Yes
5	Carpets and other floor coverings	PCE11213	Yes
5	Window coverings	PCE11214	Yes
4	Household appliances	PCE1122	—
5	Major household appliances	PCE11221	Yes
5	Small electric household appliances	PCE11222	Yes
4	Glassware, tableware, and household utensils	PCE1123	—
5	Dishes and flatware	PCE11231	Yes
5	Nonelectric cookware and tableware	PCE11232	Yes
4	Tools and equipment for house and garden	PCE1124	—
5	Tools, hardware, and supplies	PCE11241	Yes
5	Outdoor equipment and supplies	PCE11242	Yes
3	*Recreational goods and vehicles*	PCE113	—
4	Video, audio, photographic, and information processing equipment and media	PCE1131	—
5	Video and audio equipment	PCE11311	Yes
5	Photographic equipment	PCE11312	Yes
5	Information processing equipment	PCE11313	Yes
4	Sporting equipment, supplies, guns, and ammunition	PCE1132	Yes
4	Sports and recreational vehicles	PCE1133	—
5	Motorcycles	PCE11331	Yes
5	Bicycles and accessories	PCE11332	Yes
5	Pleasure boats, aircraft, and other recreational vehicles	PCE11333	Yes
4	Recreational books	PCE1134	Yes
4	Musical instruments	PCE1135	Yes
3	*Other durable goods*	PCE114	—
4	Jewelry and watches	PCE1141	—
5	Jewelry	PCE11411	Yes

Continued on next page

Table A.1 – continued from previous page

Level	Label	Code	5*
5	Watches	PCE11412	Yes
4	Therapeutic appliances and equipment	PCE1142	—
5	Therapeutic medical equipment	PCE11421	Yes
5	Corrective eyeglasses and contact lenses	PCE11422	Yes
4	Educational books	PCE1143	Yes
4	Luggage and similar personal items	PCE1144	Yes
4	Telephone and related communication equipment	PCE1145	Yes
2	Nondurable goods	PCE12	—
3	*Food and beverages purchased for off-premises consumption*	PCE121	—
4	Food and nonalcoholic beverages purchased for off-premises consumption	PCE1211	—
5	Food purchased for off-premises consumption	PCE12111	Yes
5	Nonalcoholic beverages purchased for off-premises consumption	PCE12112	Yes
4	Alcoholic beverages purchased for off-premises consumption	PCE1212	—
5	Spirits	PCE12121	Yes
5	Wine	PCE12122	Yes
5	Beer	PCE12123	Yes
4	Food produced and consumed on farms	PCE1213	Yes
3	*Clothing and footwear*	PCE122	—
4	Garments	PCE1221	—
5	Women's and girls' clothing	PCE12211	Yes
5	Men's and boys' clothing	PCE12212	Yes
5	Children's and infants' clothing	PCE12213	Yes
4	Other clothing materials and footwear	PCE1222	—
5	Clothing materials	PCE12221	Yes
5	Standard clothing issued to military personnel	PCE12222	—
5	Shoes and other footwear	PCE12223	Yes
3	*Gasoline and other energy goods*	PCE123	—
4	Motor vehicle fuels, lubricants, and fluids	PCE1231	—
5	Gasoline and other motor fuel	PCE12311	Yes
5	Lubricants and fluids	PCE12312	Yes
4	Fuel oil and other fuels	PCE1232	—
5	Fuel oil	PCE12321	Yes
5	Other fuels	PCE12322	Yes
3	*Other nondurable goods*	PCE124	—
4	Pharmaceutical and other medical products	PCE1241	—
5	Pharmaceutical products	PCE12411	Yes
5	Other medical products	PCE12412	Yes
4	Recreational items	PCE1242	—
5	Games, toys, and hobbies	PCE12421	Yes
5	Pets and related products	PCE12422	Yes
5	Flowers, seeds, and potted plants	PCE12423	Yes
5	Film and photographic supplies	PCE12424	Yes
4	Household supplies	PCE1243	—
5	Household cleaning products	PCE12431	Yes
5	Household paper products	PCE12432	Yes
5	Household linens	PCE12433	Yes
5	Sewing items	PCE12434	Yes
5	Miscellaneous household products	PCE12435	Yes
4	Personal care products	PCE1244	—
5	Hair, dental, shaving, and miscellaneous personal care products except electrical products	PCE12441	Yes

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Table A.1 – continued from previous page

Level	Label	Code	5*
5	Cosmetic / perfumes / bath / nail preparations and implements	PCE12442	Yes
5	Electric appliances for personal care	PCE12443	Yes
4	Tobacco	PCE1245	Yes
4	Magazines, newspapers, and stationery	PCE1246	—
5	Newspapers and periodicals	PCE12461	Yes
5	Stationery and miscellaneous printed materials	PCE12462	Yes
5	Expenditures abroad by U.S. residents	PCE12471	Yes
5	Less: Personal remittances in kind to nonresidents	PCE12472	—
4	Net expenditure abroad by U.S. residents	PCE1248	—
1	Services	PCE2	—
2	Household consumption expenditures (for services)	PCE21	—
3	*Housing and utilities*	PCE211	—
4	Housing	PCE2111	—
5	Rental of tenant-occupied nonfarm housing	PCE21111	Yes
5	Imputed rental of owner-occupied nonfarm housing	PCE21112	Yes
5	Rental value of farm dwellings	PCE21113	Yes
5	Group housing	PCE21114	Yes
4	Household utilities	PCE2112	—
5	Water supply and sanitation	PCE21121	Yes
5	Electricity and gas	PCE21122	Yes
3	*Health care*	PCE212	—
4	Outpatient services	PCE2121	Yes
5	Physician services	PCE21211	—
5	Dental services	PCE21212	—
5	Paramedical services	PCE21213	—
4	Hospital and nursing home services	PCE2122	—
5	Hospitals	PCE21221	Yes
5	Nursing homes	PCE21222	Yes
3	*Transportation services*	PCE213	—
4	Motor vehicle services	PCE2131	Yes
5	Motor vehicle maintenance and repair	PCE21311	—
5	Other motor vehicle services	PCE21312	—
4	Public transportation	PCE2132	—
5	Ground transportation	PCE21321	Yes
5	Air transportation	PCE21322	Yes
5	Water transportation	PCE21323	Yes
3	*Recreation services*	PCE214	—
4	Membership clubs, sports centers, parks, theaters, and museums	PCE2141	—
5	Membership clubs and participant sports centers	PCE21411	Yes
5	Amusement parks, campgrounds, and related recreational services	PCE21412	Yes
5	Admissions to specified spectator amusements	PCE21413	Yes
5	Museums and libraries	PCE21414	Yes
4	Audio-video, photographic, and information processing equipment services	PCE2142	Yes
5	Cable, satellite, and other live television services	PCE21421	—
5	Photo processing	PCE21422	—
5	Photo studios	PCE21423	—
5	Repair and rental of audio-visual, photographic, and information processing equipment	PCE21424	—
5	Video and audio streaming and rental	PCE21425	—
4	Gambling	PCE2143	—
5	Casino gambling	PCE21431	Yes

Continued on next page

Table A.1 – continued from previous page

Level	Label	Code	5*
5	Lotteries	PCE21432	Yes
5	Pari-mutuel net receipts	PCE21433	Yes
4	Other recreational services	PCE2144	—
5	Veterinary and other services for pets	PCE21441	Yes
5	Package tours	PCE21442	Yes
5	Maintenance and repair of recreational vehicles and sports equipment	PCE21443	Yes
3	*Food services and accommodations*	PCE215	—
4	Food services	PCE2151	—
5	Purchased meals and beverages	PCE21511	Yes
5	Food furnished to employees (including military)	PCE21512	Yes
4	Accommodations	PCE2152	—
5	Hotels and motels	PCE21521	Yes
5	Housing at schools	PCE21522	Yes
3	*Financial services and insurance*	PCE216	—
4	Financial services	PCE2161	—
5	Financial services furnished without payment	PCE21611	Yes
5	Financial service charges, fees, and commissions	PCE21612	Yes
4	Insurance	PCE2162	—
5	Life insurance	PCE21621	Yes
5	Net household insurance	PCE21622	Yes
5	Net health insurance	PCE21623	Yes
5	Net motor vehicle and other transportation insurance	PCE21624	Yes
3	*Other services*	PCE217	—
4	Communication	PCE2171	Yes
5	Telecommunication services	PCE21711	—
5	Postal and delivery services	PCE21712	—
5	Internet access	PCE21713	—
4	Education services	PCE2172	—
5	Higher education	PCE21721	Yes
5	Nursery, elementary, and secondary schools	PCE21722	Yes
5	Commercial and vocational schools	PCE21723	Yes
4	Professional and other services	PCE2173	—
5	Legal services	PCE21731	Yes
5	Accounting and other business services	PCE21732	Yes
5	Labor organization dues	PCE21733	Yes
5	Professional association dues	PCE21734	Yes
5	Funeral and burial services	PCE21735	Yes
4	Personal care and clothing services	PCE2174	—
5	Personal care services	PCE21741	Yes
5	Clothing and footwear services	PCE21742	Yes
4	Social services and religious activities	PCE2175	Yes
5	Child care	PCE21751	—
5	Social assistance	PCE21752	—
5	Social advocacy and civic and social organizations	PCE21753	—
5	Religious organizations' services to households	PCE21754	—
5	Foundations and grantmaking and giving services to households	PCE21755	—
4	Household maintenance	PCE2176	Yes
5	Domestic services	PCE21761	—
5	Moving, storage, and freight services	PCE21762	—
5	Repair of furniture, furnishings, and floor coverings	PCE21763	—

Continued on next page

Table A.1 – continued from previous page

Level	Label	Code	5*
5	Repair of household appliances	PCE21764	—
5	Other household services	PCE21765	—
5	Foreign travel by U.S. residents	PCE21771	—
5	Less: Expenditures in the United States by nonresidents	PCE21772	—
5	Net foreign travel (synthetic)	PCE2178	—
2	Final consumption expenditures of nonprofit institutions serving households (NPISHs)	PCE22	—
3	*Gross output of nonprofit institutions*	PCE221	—
4	Health, gross output	PCE2211	—
5	Outpatient services, gross output	PCE22111	Yes
5	Nonprofit hospitals, gross output	PCE22112	Yes
5	Nonprofit nursing homes, gross output	PCE22113	Yes
4	Recreation services, gross output	PCE2212	Yes
4	Education services, gross output	PCE2213	Yes
4	Social services, gross output	PCE2214	Yes
4	Religious organizations, gross output	PCE2215	Yes
4	Foundations and grantmaking and giving establishments, gross output	PCE2216	Yes
4	Social advocacy establishments, gross output	PCE2217	Yes
4	Civic and social organizations, gross output	PCE2218	Yes
4	Professional advocacy, gross output	PCE2219	Yes
3	*Less: Receipts from sales of goods and services by nonprofit institutions*	PCE222	—
4	Health services to households	PCE2221	—
5	Outpatient services to households	PCE22211	Yes
5	Nonprofit hospitals services to households	PCE22212	Yes
5	Nonprofit nursing homes services to households	PCE22213	Yes
4	Recreation services to households	PCE2222	Yes
4	Education services to households	PCE2223	Yes
4	Social services to households	PCE2224	Yes
4	Religious organizations' services to households	PCE2225	Yes
4	Foundations and grantmaking and giving services to households	PCE2226	Yes
4	Services of social advocacy establishments to households	PCE2227	Yes
4	Civic and social organizations' services to households	PCE2228	Yes
4	Professional advocacy services to households	PCE2229	Yes

B Lagged inflation responses found in the literature

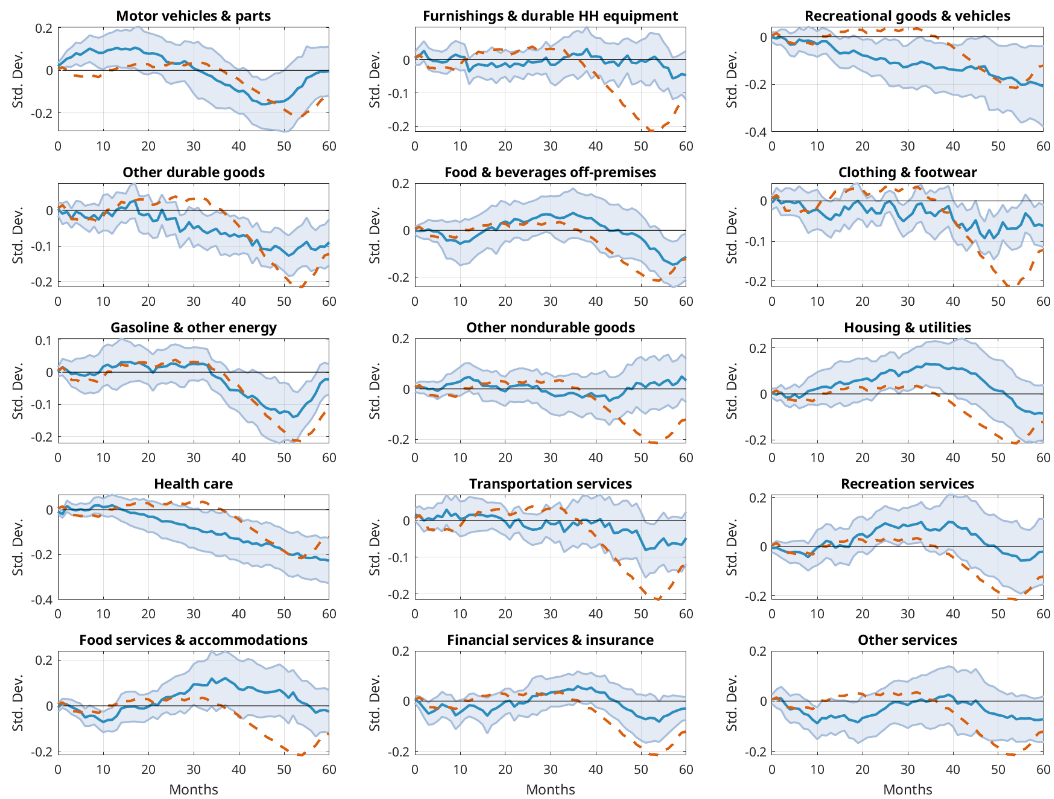
Table B.1: Responses of inflation/price level measure to monetary policy shocks

Paper	Estimator	Identification Type	Sample	Peak Response	First Negative
Jorda et al (JME, 2020)	LP-IV	Greenbook	1870 – 2006	48 (final)	27
Auclert et al (2020)	LP	Greenbook	1969:3 – 1996:12	60 (final)	44
Aruoba & Drechsel (2023)	BVAR	Greenbook	1984:2 – 2016:12	35	–
Gertler & Karadi (2015)	Proxy SVAR	High-frequency surprise	1979:7 – 2012:6	42	32
Kekre & Lenel (2022)	Proxy SVAR	High-frequency surprise	1979:7 – 2012:6	45	0
Gagliardone & Gertler (2023)	Proxy SVAR	High-frequency surprise	1973:1 – 2019:12	32	0
Jarocinski & Karadi (2020)	VAR	Sign-restricted HF	1990 – 2006	30	1
Swanson (2023)	VAR	HF surprise	1973 – 2008	20	0
Bauer & Swanson (2023)	Proxy SVAR	HF surprise	1979:7 – 2012:6	35	0
Miranda-Agrippino & Ricco (2021)	Proxy SVAR	HF surprise	1972:1 – 2014:12	24 (final)	0
Miranda-Agrippino & Ricco (2021)	Proxy SVAR	Narrative	1972:1 – 2014:12	6	–
Miranda-Agrippino & Ricco (2021)	Proxy SVAR	Informationally robust	1972:1 – 2014:12	24 (final)	0
Kaminska et al (2021)	Bayesian LP	HF surprise	1990 – 2007	0	–
Bu et al (2021)	SVAR	Fama and MacBeth (1973)	1994 – 2017	8	6
Bu et al (2021)	LP	Fama and MacBeth (1973)	1994 – 2017	8	6
Bernanke et al (2005)	FAVAR	Bernanke et al. (2005)	1959:1 – 2001:8	48	–
Adamek et al (2024)	High-dimensional LP	Bernanke et al. (2005)	1969:1 – 2008:10	20	48 (final)
Adamek et al (2024)	FAVAR	Bernanke et al. (2005)	1969:1 – 2008:10	50 (final)	50 (final)
Ramey (2016) replications:					
Christiano et al. (1999)	VAR	Recursive VAR	1965:1 – 1995:6	48 (final)	11
Coibon VAR	VAR	Narrative	1969:3 – 1996:12	42	11
Romer & Romer	LP	Narrative	1969:3 – 1996:12	48 (final)	35
Proxy SVAR	Proxy SVAR	Narrative	1969:3 – 2007:12	25	–
Gertler & Karadi SVAR	Proxy SVAR	HF surprise	1979:7 – 2012:6	38	24
Gertler & Karadi	LP	HF surprise	1990:1 – 2012:6	41	41

Notes. The responses are stated in months (columns 'Peak Response' and 'First Negative'). 'First Negative' refers to the first response that is significantly negative, based on the significance criterion chosen in each paper. HF refers to high-frequency.

C Standardized IRFs for disaggregation level 3

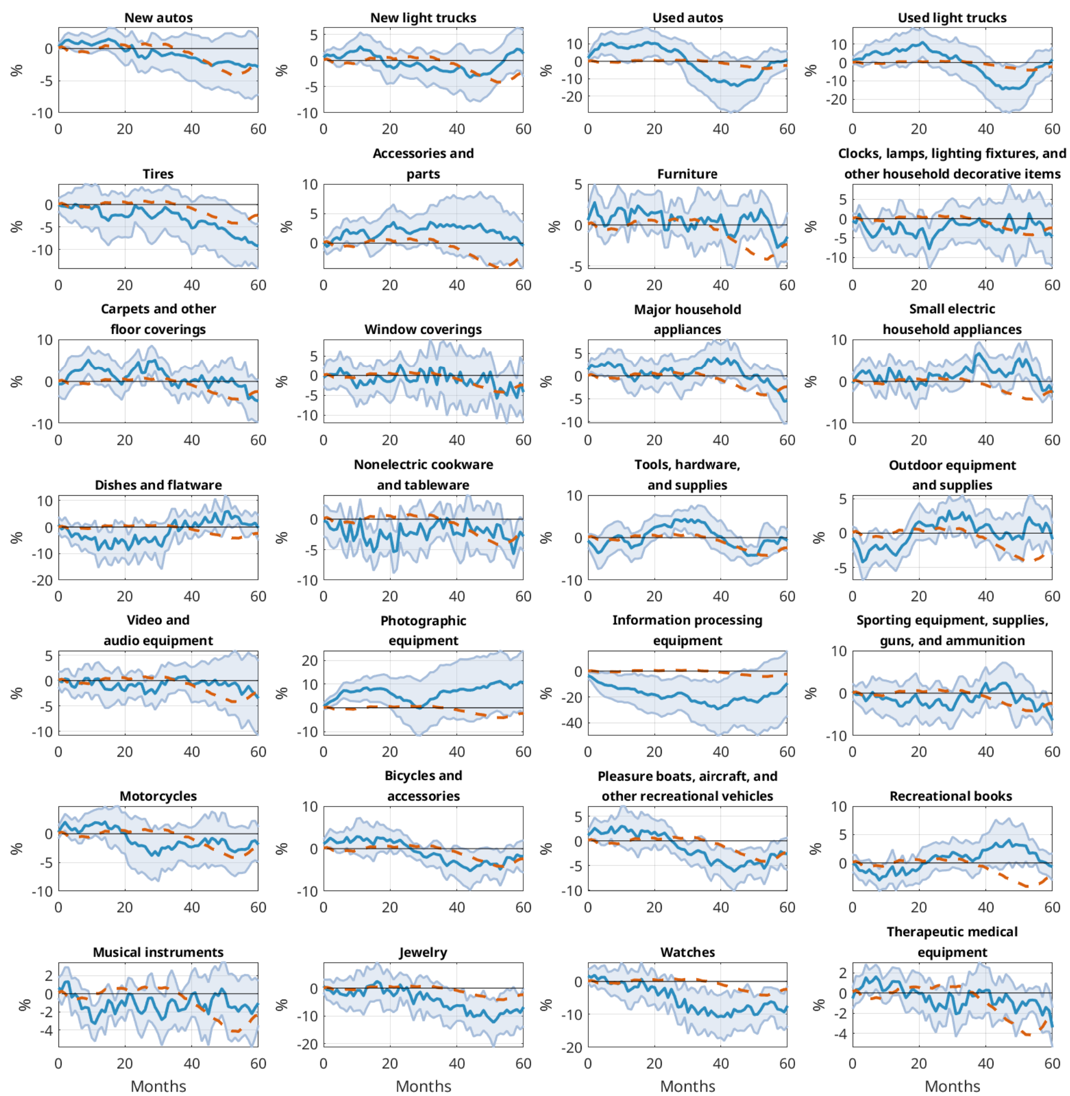
Figure C.1: IRFS TO MONETARY POLICY TIGHTENING: DISAGGREGATION LEVEL 3 (STANDARDIZED)



Notes. This figure repeats Figure 3 in the main text, but instead shows the IRFs as standardized, i.e. based on dividing each IRF by the historical standard deviation of the respective (log) price level series. The different panels make clear that the responses, for example the one of of gasoline and other energy projects, are not as large as Figure 3 might suggest, when viewed in light of the historical standard deviation of a given price series.

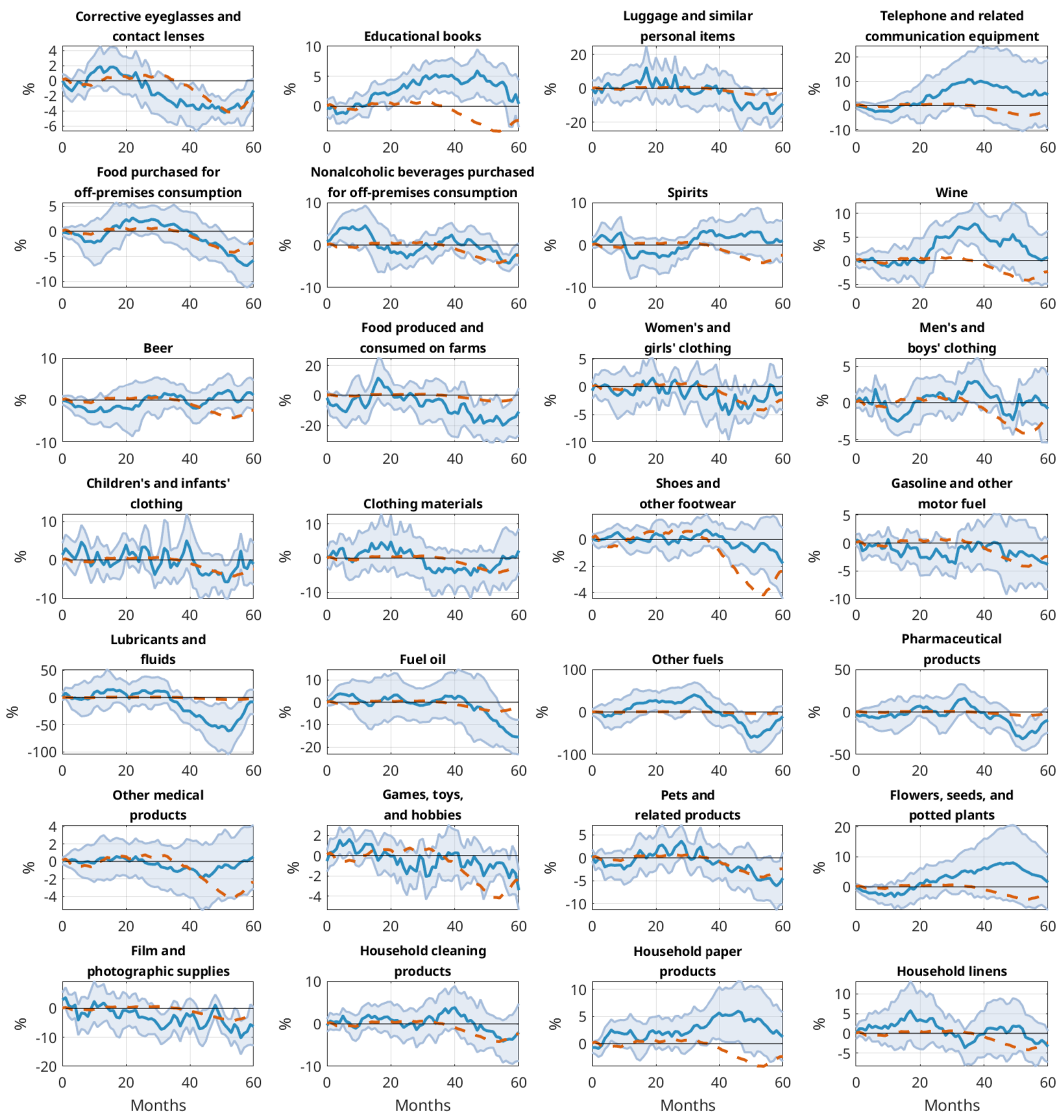
D Full set of IRFs for disaggregation level 5*

Figure D.1: IRFS TO MONETARY POLICY TIGHTENING: DISAGGREGATION LEVEL 5* (1/5)



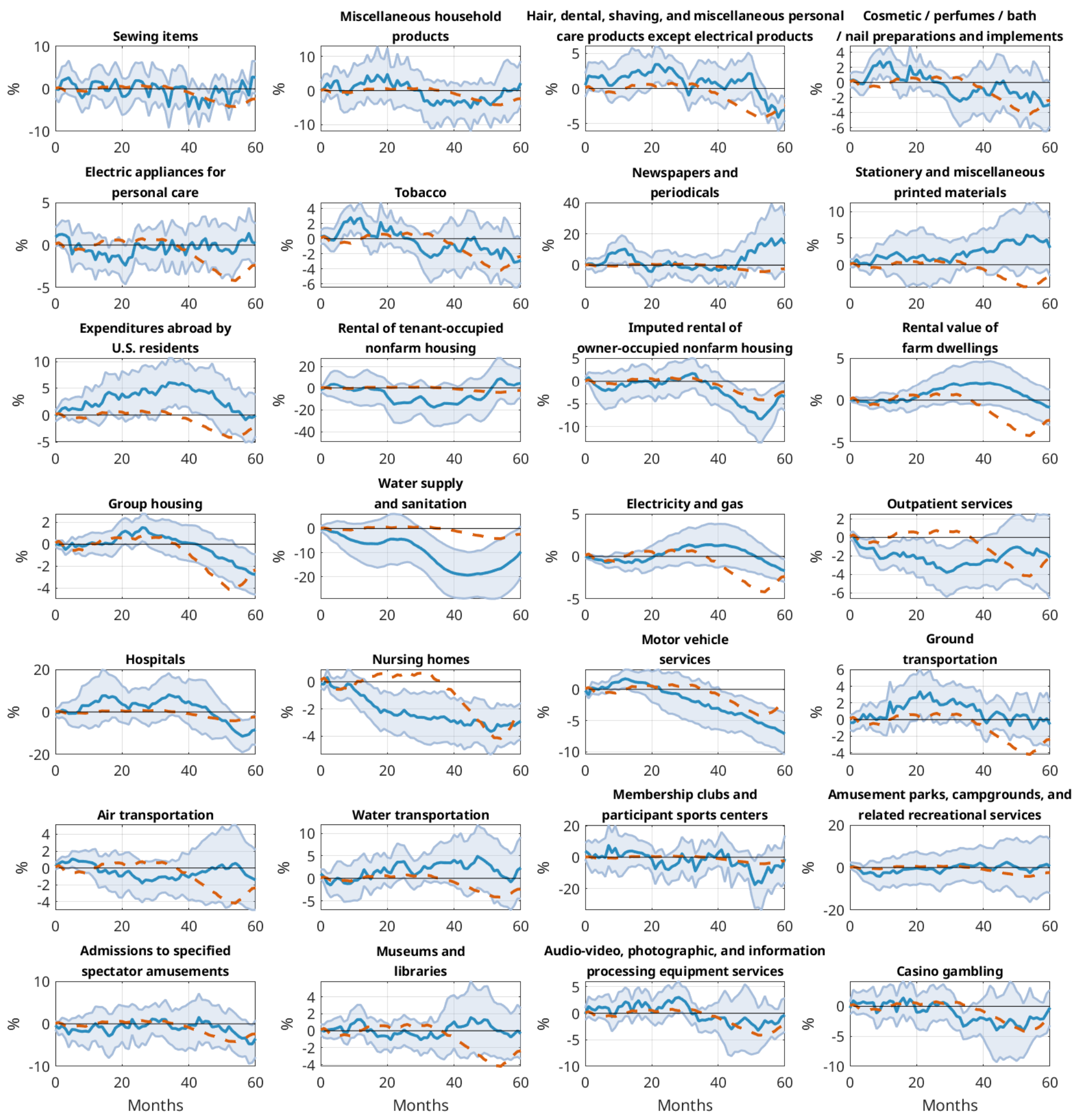
Notes. IRFs estimated using local projections using the identified monetary policy shocks of Aruoba and Drechsel (2023). This figure repeats Figure 3 but for series 1–28 at level 5*.

Figure D.2: IRFS TO MONETARY POLICY TIGHTENING: DISAGGREGATION LEVEL 5* (2/5)



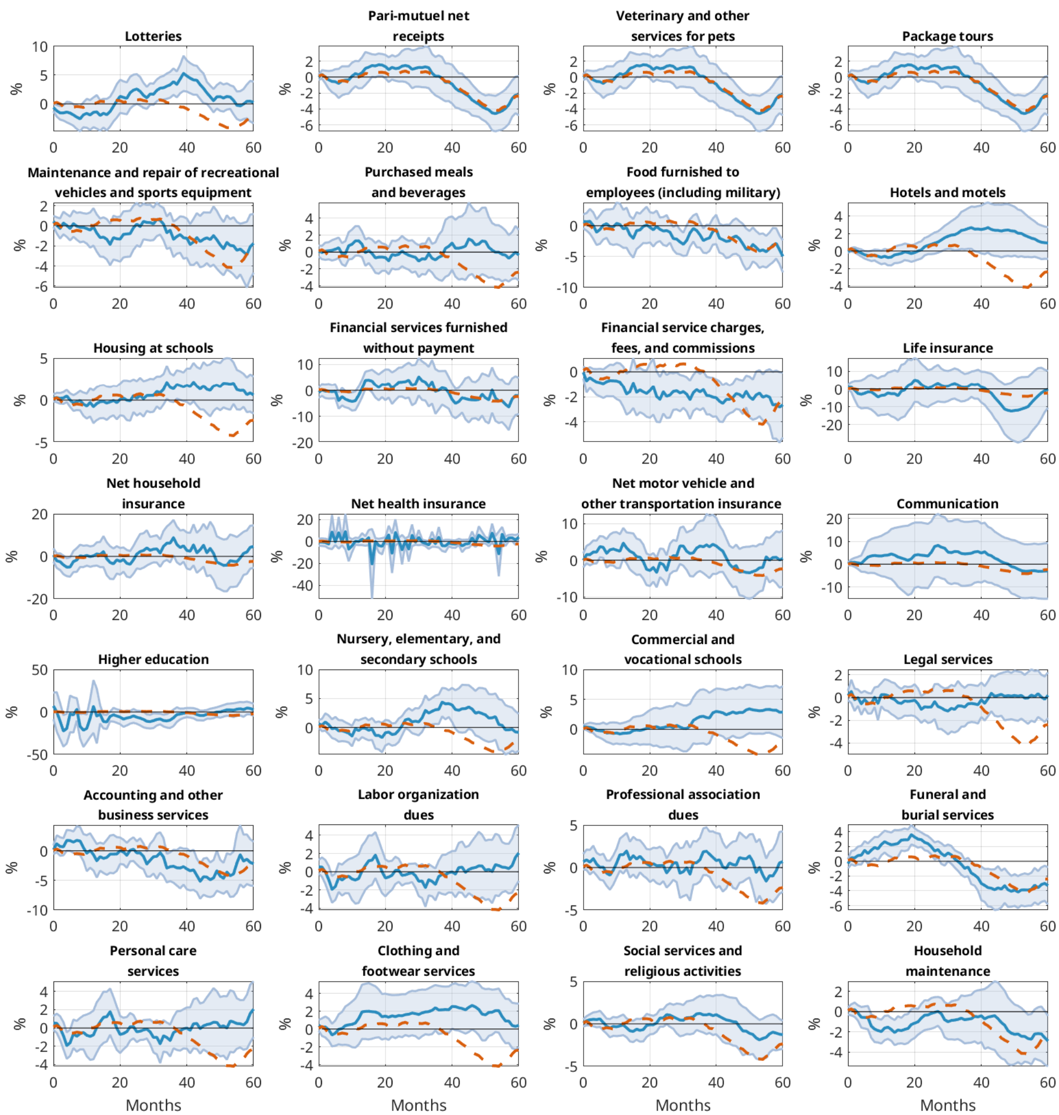
Notes. IRFs estimated using local projections using the identified monetary policy shocks of Aruoba and Drechsel (2023). This figure repeats Figure 3 but for series 29–56 at level 5*.

Figure D.3: IRFS TO MONETARY POLICY TIGHTENING: DISAGGREGATION LEVEL 5* (3/5)



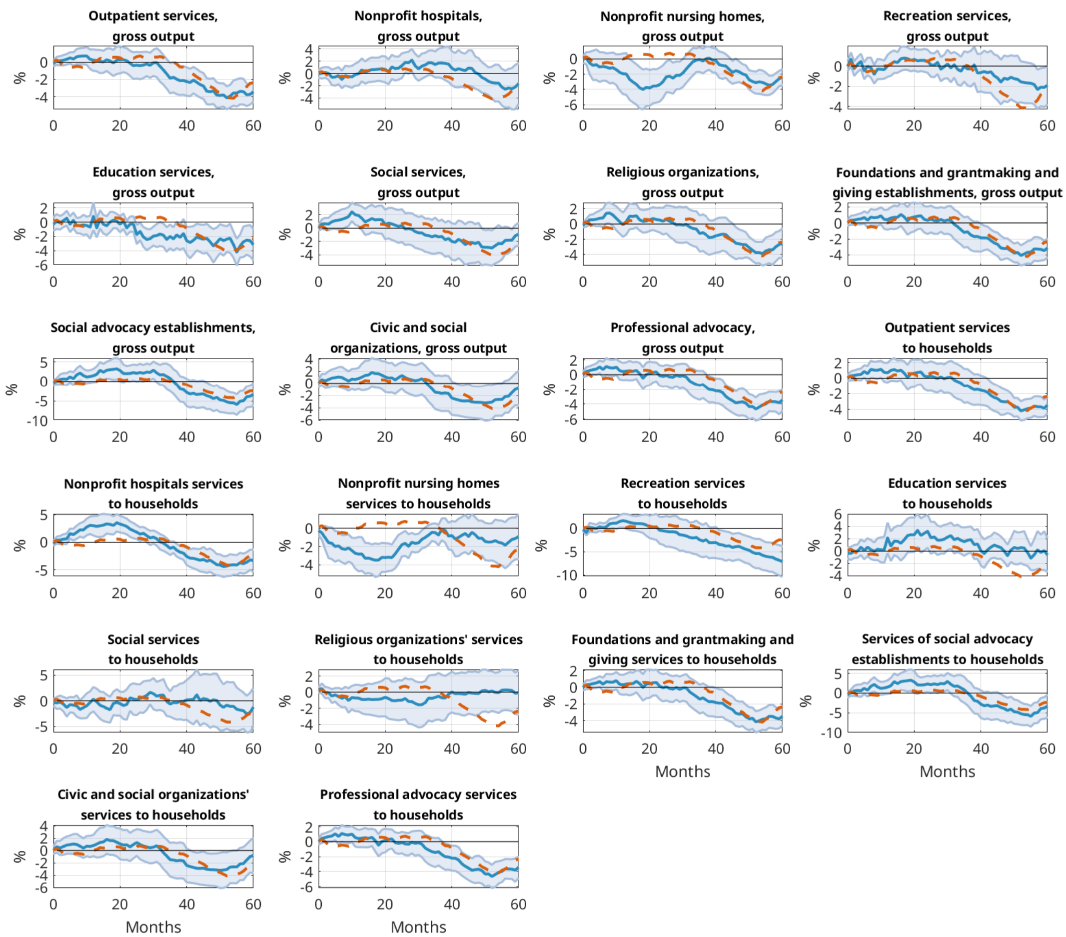
Notes. IRFs estimated using local projections using the identified monetary policy shocks of Aruoba and Drechsel (2023). This figure repeats Figure 3 but for series 57–84 at level 5*.

Figure D.4: IRFS TO MONETARY POLICY TIGHTENING: DISAGGREGATION LEVEL 5* (4/5)



Notes. IRFs estimated using local projections using the identified monetary policy shocks of Aruoba and Drechsel (2023). This figure repeats Figure 3 but for series 85–113 at level 5*.

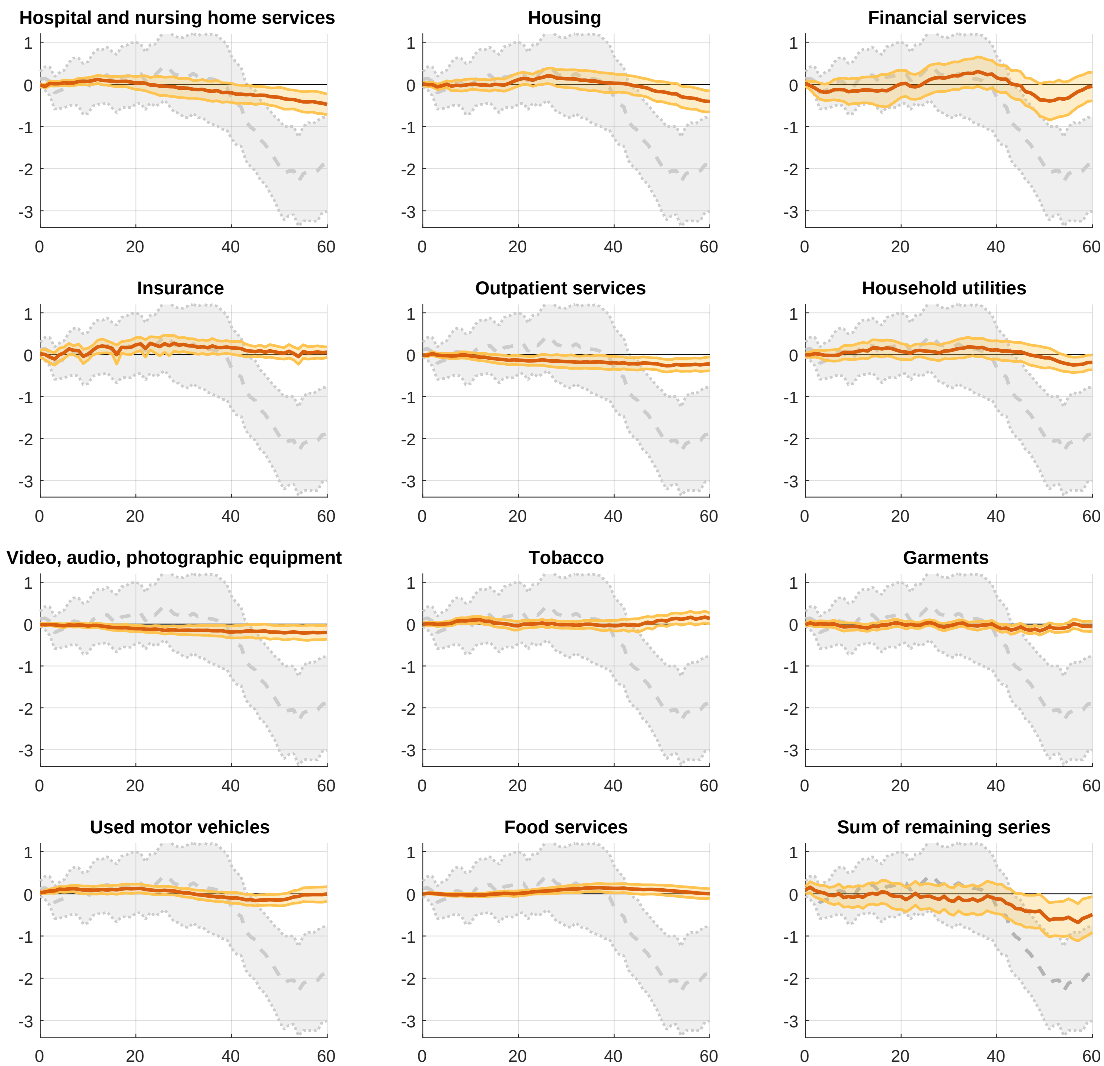
Figure D.5: IRFS TO MONETARY POLICY TIGHTENING: DISAGGREGATION LEVEL 5* (5/5)



Notes. IRFs estimated using local projections using the identified monetary policy shocks of Aruoba and Drechsel (2023). This figure repeats Figure 3 but for series 114–136 at level 5*.

E Contribution IRFs for core inflation

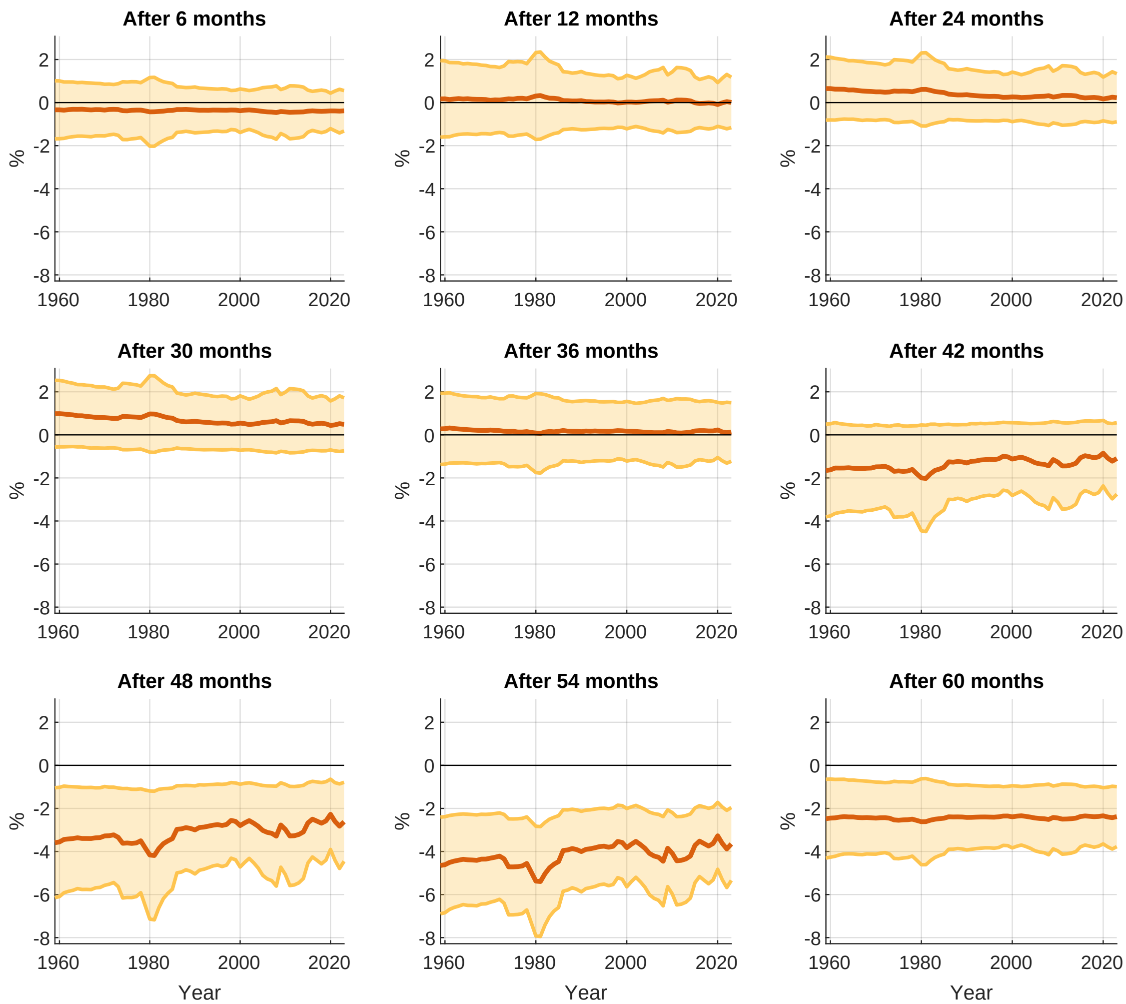
Figure E.1: IRFS TO MONETARY POLICY TIGHTENING: CONTRIBUTION SERIES FOR CORE PCE



Notes. This figure repeats Figure 5 from the main text, but for core instead of headline PCE.

F Re-aggregation using year-by-year weights

Figure F.1: UNPACKING THE IRF AGGREGATION THROUGH TIME



Notes: Re-aggregated Level 3 responses using year-by-year expenditure weights, for separate IRF horizons. The x axis shows the year used for re-aggregation and the different subplots correspond to different IRF horizon. The solid line corresponds to the points estimates and the shaded areas correspond to 90% significance bands based on HAC standard errors and accounting for cross-sectional dependence using SUR. These plots make clear that despite some meaningful changes in expenditure shares shown in Figure 9, the aggregated responses look fairly stable through time.