BANCA D'ITALIA
EUROSISTEMA

Questioni di Economia e Finanza

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The series is available online at www.bancaditalia.it .

ISSN 1972-6627 (print)
ISSN 1972-6643 (online)

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

OIL PRICE PASS-THROUGH INTO CORE INFLATION

by Cristina Conflitti* and Matteo Luciani**

Abstract

This work estimates the effect that fluctuations in oil prices have on changes in consumer prices in both the United States and the euro area. For many of the basic items in the basket of goods used to estimate inflation, the effects of oil price trends are divided into two components: the first is linked to the specific characteristics of individual products (such as, for example, the importance of energy in the production process), while the second is related to macroeconomic factors which are in turn connected with changes in oil prices. The results show that changes in oil prices mainly pass through to core inflation (or rather to inflation excluding food and energy products) by means of macroeconomic factors; while the effect is limited, it is statistically different from zero and persists over time.

JEL Classification: C32, E31, E32, Q43.
Keywords: core inflation, oil price, dynamic factor model, pass-through, disaggregate consumer prices.

Contents

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1 Introduction

Quantifying the magnitude and establishing the timing of the pass-through of oil price changes to consumer prices is crucial for forecasting inflation, particularly in light of the fact that oil prices tend to undergo wide fluctuations. Consider the recent plunge of oil prices from July 2014 to February 2016, from about $100 per barrel to $30. What is the effect of such a large fall in oil prices on core inflation? And how long will this effect last? In this paper, by using a novel econometric approach, we answer these questions and conclude that oil price fluctuations have a small, but non negligible, and long lasting effect on core inflation. According to our estimates the recent plunge in oil prices shaved-off just a couple of tenths of a percentage point to core inflation in both the US and the euro area, but this effect is far from being fully absorbed and will only vanish by 2020.

Oil price fluctuations affect consumer inflation through both its energy component and the non-energy components. However, while there is clear evidence that the pass-through from oil prices to energy prices is relatively fast and complete (Burdette and Zyren, 2003; Meyler, 2009), though it is still to be determined whether it is symmetric or not (Venditti, 2013; Atil et al., 2014; Chesnes, 2016), it is unclear to what degree changes in oil prices pass-through into non-energy prices (Kilian and Lewis, 2011; Kilian, 2014).

In theory, an increase in oil prices might have an inflationary effect in at least four ways. First, because energy prices represent a portion (sometimes considerable) of production costs. Second, because it might lead workers to demand a higher wage to compensate for the increase in energy prices (Blanchard and Gali, 2007). Third, because it might mimic an adverse supply shock if real wages do not decrease sufficiently thus triggering an adjustment in employment (Bruno and Sachs, 1985). Fourth, because, as a consequence of the above, it likely affects inflation expectations. By contrast, an increase in oil prices may have a modest, compared to the effects above, deflationary effect because higher energy prices tend to reduce net-disposable income, and thus consumption (Edelstein and Kilian, 2009) and investments (Edelstein and Kilian, 2007).

Empirically, extensive evidence suggests that changes in the oil prices contribute to macroeconomic fluctuations (see Hamilton, 1983, 2003; Hooker, 1996; Barsky and Kilian, 2002; Kilian, 2008, among others). Various authors have shown that the pass-through of oil price changes to core prices has however declined since the mid-eighties (see Hooker, 2002; Chen, 2009; Clark and Terry, 2010, among others), up to the point that it now is very small if not nil (for example Cavallo, 2008; Clark and Terry, 2010).

In this paper we use a novel approach to estimate the oil price pass-through into core consumer prices. We first estimate a dynamic factor model on a panel of disaggregate prices, which allows us to disentangle *common* changes in disaggregate prices, from *idiosyncratic* ones. We next use VAR techniques to estimate the oil price pass-through via the *common* component, as well as via the *idiosyncratic* component. Both these pass-throughs are likely to be important: to the extent that oil prices contribute to macroeconomic fluctuations they may pass-through into core inflation via the *common*/macroeconomic component; they may pass-through into core inflation also via the *idiosyncratic* components, with different intensities due, e.g., to the share of energy in production.

Our empirical analysis is first carried out on a panel of US personal consumption expenditure (PCE) disaggregate price indexes from 1984 to 2016. We show that *common* and *idiosyncratic* dynamics in disaggregate prices have different statistical properties: *common* dynamics are slow moving, *idiosyncratic* dynamics are fast moving and volatile. Disentangling these two components proves crucial when estimating the oil price pass-through into core inflation, as the estimated pass-through into the *idiosyncratic* component is not statistically different from zero, whereas the pass-through via the *common* component is small, but statistically different from zero, non negligible and long lasting.

The subsample analysis confirms, as found in the literature, that the oil price pass–through into core inflation has decreased over time. However, in contrast with some contributions (for example Clark and Terry, 2010), we always find a positive and statistically significant pass-through—the reason presumably being that by disentangling between *common* and *idiosyncratic* components, we do not let the noisy *idiosyncratic* component affect our estimation results.

Finally, we estimate the oil price pass-through on a panel of euro area harmonized indexes of consumer prices (HICP). These estimates yield a euro area pass-through similar to that of the US.

Other papers have used dynamic factor models to study the effects of oil price fluctuations on the economy, but none have focused on the pass-through into consumer prices. For example, Aastveit (2014), Aastveit et al. (2015), Juvenal and Petrella (2015), and Stock and Watson (2016) study the effects of different structural oil price shocks on the economy, while An et al. (2014) study whether oil price shocks have asymmetric effects on the economy. Moreover, other papers have used dynamic factor models to analyze disaggregate prices (Cristadoro et al., 2005; Altissimo et al., 2009; Boivin et al., 2009; Reis and Watson, 2010, among others), but none have used these models to study the oil price pass-through. Finally, Gao et al. (2014) study the effect of oil price shocks on a number of disaggregate US consumer prices using VAR techniques; they find a significant effect only on the price of energy-intensive goods but do not distinguish between macroeconomic and idiosyncratic effects.

The rest of the paper proceeds as follows. Section 2 presents the methodology. Section 3 presents the empirical analysis on the US, namely: Section 3.1 describes the data used, and Section 3.2 discusses common and idiosyncratic dynamics in US PCE prices. Then, Section 3.3 presents estimates of the oil price pass-through, Section 3.4 presents subsample analysis, and Section 3.5 presents estimates obtained with a more structural model. Finally, Section 4 presents the empirical analysis on the euro area, and Section 5 briefly summarizes the results.

2 The econometric framework

The goal of this paper is to quantify the effect of oil price changes on core, energy, and food price inflation. More precisely, we aim to disentangle the specific (*idiosyncratic*) effect that an oil price change might have on each disaggregate price, from its overall (*common*) effect that an oil price change has on all prices. To do so, we first estimate a dynamic factor model on a panel of price indicators to separate common from idiosyncratic price changes, and then use VAR techniques to estimate the pass-through.

Factor models are based on the idea that fluctuations in disaggregate prices are due to a few common (macroeconomic) shocks ($\mathbf{u}_t$) that affect all prices, and to several idiosyncratic shocks ($\mathbf{e}_t$), resulting from sector-specific dynamics or from sampling error, which influence one or a few of them. Accordingly, each price component in the dataset can be decomposed into a common part χ_{it}, which is a linear combination of a small number r of common factors $\mathbf{f}_t$ that are driven by the common shocks, and an idiosyncratic part ξ_{it} that is driven by idiosyncratic shocks. Let $\pi_{it} = 1200 \times \log(\frac{P_{it}}{P_{it-1}})$ be the annualized month-on-month log-change in the i-th price component at time t, where $i = 1, ..., n$ and $t = 1, ..., T$, we then have

$$\pi_{it} = \boldsymbol{\lambda}_i' \mathbf{f}_t + \xi_{it} \tag{1}$$

where $\boldsymbol{\lambda}_i$ is a $r \times 1$ vector containing the factor loadings of the i-th variable, and $\chi_{it} = \boldsymbol{\lambda}_i' \mathbf{f}_t$. Model (1) is the approximate dynamic factor model proposed by Stock and Watson (2002a,b), which is a particular case of the generalized dynamic factor model studied by Forni et al. (2000) and Forni and Lippi (2001).

It is well documented that changes in the oil price contribute to macroeconomic fluctuations (see Hamilton, 1983, 2003; Hooker, 1996; Barsky and Kilian, 2002; Kilian, 2008, among others), thus they are likely to have a *macroeconomic* effect on all prices. To incorporate this feature in our model, we assume that the common factors and the oil price evolve over time according to a VAR model. Let $y_t = \Delta \log(\frac{oil_t}{price_t})$ be the monthly real oil price growth rate, then we have

$$\mathbf{A}(L) \begin{pmatrix} \mathbf{f}_t \\ y_t \end{pmatrix} = \begin{pmatrix} \mathbf{u}_t \\ v_t \end{pmatrix} \tag{2}$$

where v_t is "the oil price shock".[1]

At the same time, given that sectors are more or less energy intensive so that energy costs represent a larger or smaller share of total costs, a change in the oil price might have a very different effect on disaggregate prices depending on how energy intensive is the production of each single item. This points at the possibility of idiosyncratic effects of oil price changes on each price component, and therefore we assume that the oil price and each idiosyncratic component evolve over time according to a bivariate VAR:

$$\mathbf{B}_i(L) \begin{pmatrix} \xi_{it} \\ y_t \end{pmatrix} = \begin{pmatrix} e_{it} \\ v_t \end{pmatrix} \tag{3}$$

By comparing (2) and (3) we can see that there is a conflict between these two equations in that the changes in the oil prices are specified in two different ways, namely:[2] $y_t =$

[1]Our model is very similar to a standard FAVAR model (Bernanke et al., 2005), which in its turn is a restricted version of the structural dynamic factor model first introduced by Giannone et al. (2005), Stock and Watson (2005), and Forni et al. (2009). In a FAVAR model the oil price is treated as an observed factor, which means that the oil price is part of the common space only, while not having any effects on the idiosyncratic component. In formulas, equation (1) is replaced by $\pi_{it} = \boldsymbol{\lambda}_i'\mathbf{f}_t + \gamma_i y_t + \xi_{it}$, while (2) stays the same and the idiosyncratic component is not modelled. As a robustness check, in Appendix B we show the estimated pass-through when a FAVAR model is used.

[2]In what follows we use the notation according to which $\mathbf{A}(L) = \mathbf{I} - \mathbf{A}_1 L - \mathbf{A}_2 L^2 - \dots \mathbf{A}_p L^p =$

$a_{22}(L)y_{t-1} + \mathbf{a}_{21}(L)\mathbf{f}_{t-1} + v_t$ from (2), and $y_t = b_{i22}(L)y_{t-1} + b_{i21}(L)\xi_{it-1} + v_t$, for $i = 1, \dots, n$, from (3). It is therefore clear that, in order for (2) and (3) to simultaneously hold, restrictions on $\mathbf{A}(L)$ and $\mathbf{B}_i(L)$ must be imposed. It turns out that the only possible restriction is to impose that $\mathbf{a}_{21}(L) = \mathbf{0}$ and $b_{i21}(L) = 0$,[3] so that:

$$\mathbf{A}(L) = \begin{pmatrix} \mathbf{I} - \mathbf{a}_{11}(L) & -\mathbf{a}_{12}(L) \\ \mathbf{0} & 1 - a_{22}(L) \end{pmatrix} \quad \text{and} \quad \mathbf{B}_i(L) = \begin{pmatrix} 1 - b_{i11}(L) & -b_{i12}(L) \\ 0 & 1 - b_{i22}(L) \end{pmatrix}$$

with $a_{22}(L) = b_{i22}(L)$, which yields

$$y_t = a_{22}(L)y_{t-1} + v_t. \tag{4}$$

Equation (4) clarifies two things: first in our framework the oil price is exogenously determined, that is it is not caused by US or euro area economy. In the literature, oil price shocks are often identified by assuming that energy prices are predetermined with respect to the US/EA economy at monthly frequency (for a thorough discussion of this identification strategy see Kilian and Vega, 2011), which in practice means using a Choleski decomposition with the oil price ordered first (for example Gao et al., 2014; Stock and Watson, 2016). The restriction in (4) is in the same spirit, though stronger, as we are imposing that the oil price is exogenous, rather than predetermined, to US/EA prices.

Second, "the oil price shock" v_t is nothing else than a residual from an AR model, and as such it has no structural interpretation, that is we do not disentangle between oil supply and oil demand shocks (a non exhaustive list of papers that do so is: Barsky and Kilian,

$\mathbf{I} - \boldsymbol{\mathcal{A}}(L)$, where $\boldsymbol{\mathcal{A}}(L)$ is conveniently partitioned in four polynomials $\mathbf{a}_{11}(L)$, $\mathbf{a}_{12}(L)$, $\mathbf{a}_{21}(L)$, and $a_{22}(L)$ of dimensions $r \times r$, $r \times 1$, $1 \times r$, and 1×1, respectively. The same notation is used for $\mathbf{B}(L)$. Furthermore, let $\mathbf{C}(L) = \mathbf{A}(L)^{-1}$ be the MA representation of (2), then we use the notation $\mathbf{C}(L) = \mathbf{I} + \mathbf{C}_1 L - \mathbf{C}_2 L^2 + \dots = \mathbf{I} + \boldsymbol{\mathcal{C}}(L)$, where $\boldsymbol{\mathcal{C}}(L)$ is conveniently partitioned in four polynomials $\mathbf{c}_{11}(L)$, $\mathbf{c}_{12}(L)$, $\mathbf{c}_{21}(L)$, and $c_{22}(L)$. The same notation is used for $\mathbf{D}(L) = \mathbf{B}(L)^{-1}$.

[3] While from a theoretical point of view imposing this restriction is necessary, from an empirical point of view it is nearly irrelevant. Indeed, the estimated pass-through obtained without imposing this restriction is essentially the same as that reported in Section 3 and 4.

2002, 2012; Kilian, 2009; Lippi and Nobili, 2012; Baumeister and Peersman, 2013).

Under the assumption that all the components of $\boldsymbol{\pi}_t$ are stationary, the common factors, the factor loadings, and the idiosyncratic components can be estimated by principal components (Stock and Watson, 2002a; Bai, 2003).[4] Once the factors and the idiosyncratic components are estimated, the VAR in (2) and the n VARs in (3) can be estimated by OLS simply by replacing $\mathbf{f}_t$ and ξ_{it} with their principal components estimates, with the estimated parameters converging at the standard rate $\min(\sqrt{N}, \sqrt{T})$ (Forni et al., 2009).

Once $\mathbf{A}(L)$ and $\mathbf{B}_i(L)$ are estimated, by defining $\mathbf{C}(L) = \mathbf{A}(L)^{-1}$ and $\mathbf{D}_i(L) = \mathbf{B}_i(L)^{-1}$, where

$$\mathbf{C}(L) = \begin{pmatrix} \mathbf{I} + \mathbf{c}_{11}(L) & \mathbf{c}_{12}(L) \\ \mathbf{0} & 1 + c_{22}(L) \end{pmatrix}, \quad \text{and} \quad \mathbf{D}_i(L) = \begin{pmatrix} 1 + d_{i11}(L) & d_{i12}(L) \\ 0 & 1 + d_{i22}(L) \end{pmatrix},$$

and by substituting (2) and (3) in (1) we get

$$\begin{aligned} \pi_{it} &= \left(\boldsymbol{\lambda}_i \mathbf{c}_{12}(L) + d_{i12}(L)\right) v_t + \boldsymbol{\lambda}_i \mathbf{c}_{11}(L)\mathbf{u}_t + (1 + d_{i11}(L))e_{it} \\ &= \psi_i^{\chi}(L)v_t + \psi_i^{\xi}(L)v_t + \boldsymbol{\phi}_i(L)\mathbf{u}_t + \theta_i(L)e_{it} \end{aligned} \tag{5}$$

where $\psi_i^{\chi}(L)$ and $\psi_i^{\xi}(L)$ measure, respectively, the *common* and the *idiosyncratic* pass-through of an unexpected and unpredictable change in the real oil price to the inflation rate of price i.

Having computed the oil price pass-through into each disaggregate price, we can construct the pass-through into core price inflation as:

$$\psi_c(L) = \sum_{i \in core} w_i \psi_i^{\chi}(L) + \sum_{i \in core} w_i \psi_i^{\xi}(L) = \psi_c^{\chi}(L) + \psi_c^{\xi}(L)$$

[4]Estimation of the factors when the data are $I(1)$ is examined by Bai (2004), Bai and Ng (2004), and Barigozzi et al. (2016). Estimation of impulse response functions for non stationary dynamic factor models is considered in Barigozzi et al. (2016).

and likewise for energy price inflation and food price inflation simply by selecting the appropriate prices and weights.

3 Oil price pass-through into inflation in the US

3.1 Data

The price data for the US are monthly price indexes for personal consumption expenditures (PCE) by type of product. The data are taken from the NIPA Table 2.4.4U from the Bureau of Economic Analysis and downloaded from Haver.

Price data are available at different levels of disaggregation, the finest of which includes more than 200 price indexes (see Dolmas, 2005, for further details). However, for the purpose of our analysis 200+ series correspond to an unnecessary high level of detail, and, therefore, we chose a lower level of aggregation comprising 88 price indexes (the complete list of series is available in Appendix A). In this dataset 65% of the price indexes have a weight smaller than $\frac{1}{100}$, and just 16% of them have a weight larger than $\frac{2}{100}$.

To estimate the pass-through into the aggregates for core, energy, and food inflation we compute PCE weights as (see Dolmas, 2005, for details):

$$w_{i,t+1} = 0.5\frac{Q_{it}P_{it}}{\sum Q_{it}P_{it}} + 0.5\frac{Q_{i,t+1}P_{it}}{\sum Q_{i,t+1}P_{it}}, \tag{6}$$

in which data for Q_{it} are taken from the NIPA Table 2.4.6U. In other words, the weights for the i-th item in, say, June 2016 is equal to an average of the expenditure share of that item in May 2016 and its expenditure share had it been bought in June 2016 at May 2016 prices. However, although PCE weights change every month, for the purpose of estimation of the oil price pass-through into core, energy, and food price inflation we need just one set of weights, and we choose to pick the last one available, which are the weights for June

2016.

Finally, the oil price is measured by the West Texas Intermediate (WTI) spot crude oil price, which is deflated by the core PCE price index.[5] The data for WTI are from the US Energy Information Administration and the Chicago Mercantile Exchange and they were downloaded from Haver (PZTEXP@USECON), while the core PCE price index is from the NIPA table (ID 368, Name DPCCRX).

3.2 Common and idiosyncratic dynamics in PCE prices

In this Section we look at common and idiosyncratic dynamics in PCE prices with the ultimate goal of selecting the number of common factors, r, to be included in our model. The results are obtained on a sample starting in 1984:M1 and ending in 2016:M6 (see Section 3.3 for a discussion on the choice of the sample).

Table 1 shows the percentage of overall variance explained by the first ten factors. The first factor explains a good chunk (8%) of the total variability in the dataset, while the other factors explain just a residual fraction of it. Thus, the numbers in Table 1 provide strong evidence pointing towards the existence of one common factor, but it is unclear if additional factors are needed.

Table 1: Common dynamics in PCE prices

r	1	2	3	4	5	6	7	8	9	10
μ_t	7.9	4.3	3.2	3.0	2.7	2.5	2.4	2.2	2.1	2.0

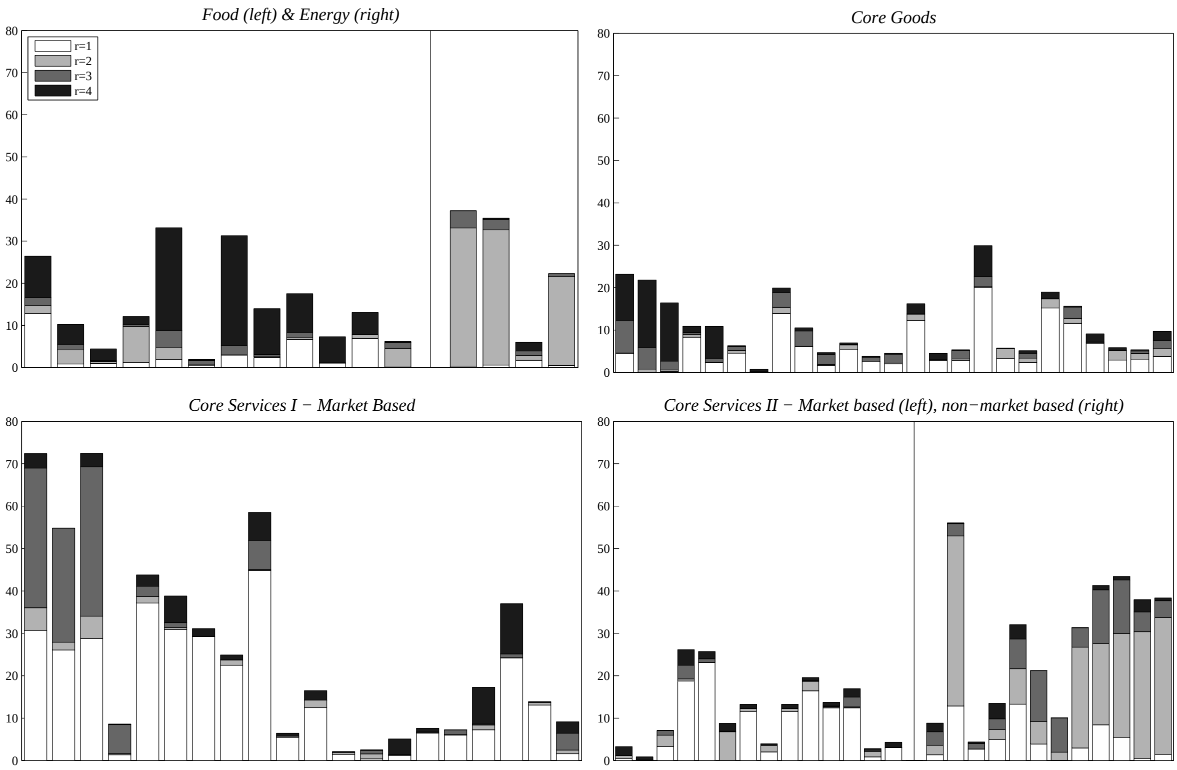
Notes: μ_t is the percentages of total variance explained by the first r factors.

Figure 1 shows the percentage of variance of each variable explained by the first four factors, where we have divided the disaggregate prices into four plots each of which rep-

[5] Blanchard and Gali (2007) argue that some of the oil price changes are extremely large and thus might bias the estimation of the oil price equation. We checked this issue by running on the real oil price growth rate the same procedure to remove outliers that we run on disaggregate prices (see Appendix A for details), and we found just one outlier in 1974:M1. Removing that outlier does not change any of the results shown in the paper.

resents a different category. If we look at food and energy, which we expect to be driven to a great extent by sectoral factors, such as weather in the case of food and various supply shocks in the case of energy, we see that the second and the fourth factor have good explanatory power thus suggesting that they capture mainly idiosyncratic food/energy related fluctuations. If we look at "Core Goods" prices", Core Services I" prices, and "Core Services II" (market-based) prices, the second, the third, and the fourth factor have a very low explanatory power suggesting that one factor suffices for these categories.

Figure 1: Common dynamics in PCE prices



Notes: This figure shows the percentage of variance (y-axis) of each variable (x-axis) explained by the first four factors. Each bar represent a different disaggregate price. Core Services I includes: "Housing and utilities", "Health care", "Transportation services", "Recreation services", "Food services and accommodations". Core Services II includes: "Financial services and insurance", "Other services", and "Final consumption expenditures of NPISHs".

The results in Table 1 and Figure 1 point out that, independently of the number of factors included in the model, idiosyncratic dynamics are the main driver of changes in disaggregate PCE prices (see also Boivin et al., 2009; Reis and Watson, 2010). However, although idiosyncratic dynamics dominate disaggregated prices' fluctuation, they do not dominate the evolution of the aggregate core index. Indeed, in a model with one common factor, the common component accounts for 57% of core PCE fluctuation. Furthermore, the stochastic properties of the common and idiosyncratic components are different: the former are very persistent, while the latter tend to have very short memory (see Table 2). Note that these last two results are in line with the theoretical results in Zaffaroni (2004). Zaffaroni (2004) shows that, as the number of variables gets large, the aggregation of univariate heterogeneous ARMA processes driven by a common and an idiosyncratic shock yields a time series that (1) is more persistent than the disaggregate series, and (2) is mainly driven by the common shock; by contrast the disaggregated series are mainly driven by the idiosyncratic shocks (see also Granger, 1980). For empirical results similar to ours, see Clark (2006) and Maćkowiak et al. (2009) for the U.S., and Altissimo et al. (2009) and Beck et al. (2016) for the euro area.

In summary, there is strong evidence indicating that PCE prices admit a factor representation, but there is high uncertainty on the number of factors to be included in the model. Furthermore, this uncertainty is not resolved even by resorting to more formal criteria, such as, for example, the Bai and Ng (2002) information criteria that support the choice of up to three common factors.

Table 2: Persistence of common and idiosyncratic dynamics

	ρ_1	ρ_6	ρ_{12}
$\rho_j^\xi(50)$	0.12	0.07	0.06
$\rho_j^\xi(75)$	0.22	0.12	0.12
$\rho_j^\xi(90)$	0.38	0.21	0.21
ρ_j^f	0.79	0.75	0.70

Notes: This table shows the persistence of the idiosyncratic components and the common factor. In detail, $\rho_j^\xi(\alpha)$ is the α percentile of the distribution of the estimated autocorrelation coefficient at lag j of the idiosyncratic component, while ρ_j^f is the estimated autocorrelation coefficient at lag j for the common factor.

3.3 Oil price pass-through

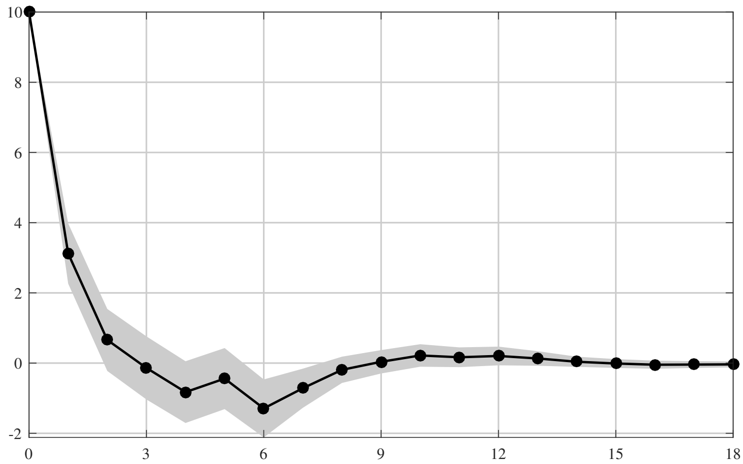
This Section presents estimates of the oil price pass-through into core PCE price inflation, food PCE price inflation, and energy PCE price inflation. Results for each of the 88 PCE price indexes in our dataset are available in an online appendix.

Our benchmark specification includes one factor ($r = 1$), and six lags for the VARs (2) and (3). As discussed in Section 3.2 there is considerable uncertainty surrounding the appropriate number of factors. We took a conservative approach under the rationale that the existence of one factor is almost sure, while the presence of additional factors is not so sure (results with $r = 3$ are available in Appendix B). The choice of six lags, despite being larger than what selected by standard information criteria, is in line with the existing literature (see for example Edelstein and Kilian, 2009; Gao et al., 2014).

The model is estimated on a sample starting in 1984:M1 and ending in 2016:M6, which contrasts with a large part of the literature on oil price shocks that uses samples starting in 1973/1974 (for example Kilian, 2009; Aastveit, 2014; Gao et al., 2014). There are at least two good reasons to consider a sample starting in 1984 rather than 1974. First, it is well known that during the 1970s and the early 1980s inflation was much more volatile than afterwards. Second, inflation in the 70s was heavily influenced by a number of food price shocks, and by the 1971-1974 wage and price controls (see Blinder and Rudd, 2013). These "structural breaks" are capable of distorting our estimates, and actually several authors (for example Hooker, 2002; Clark and Terry, 2010) found a structural break in the oil–inflation relation. For these reasons our sample starts in 1984, the year considered by the literature as the start of the "great moderation".

Figure 2 shows the impulse response function to an oil price shock of the percentage change of the real oil price, together with a bootstrapped 90% confidence interval. After an unexpected 10% increase, the real oil price increases further in the next two months by approximately 3% and $\frac{1}{2}$%, respectively.

Figure 2: Impulse response function to an oil price shock
Percentage change of the real oil price



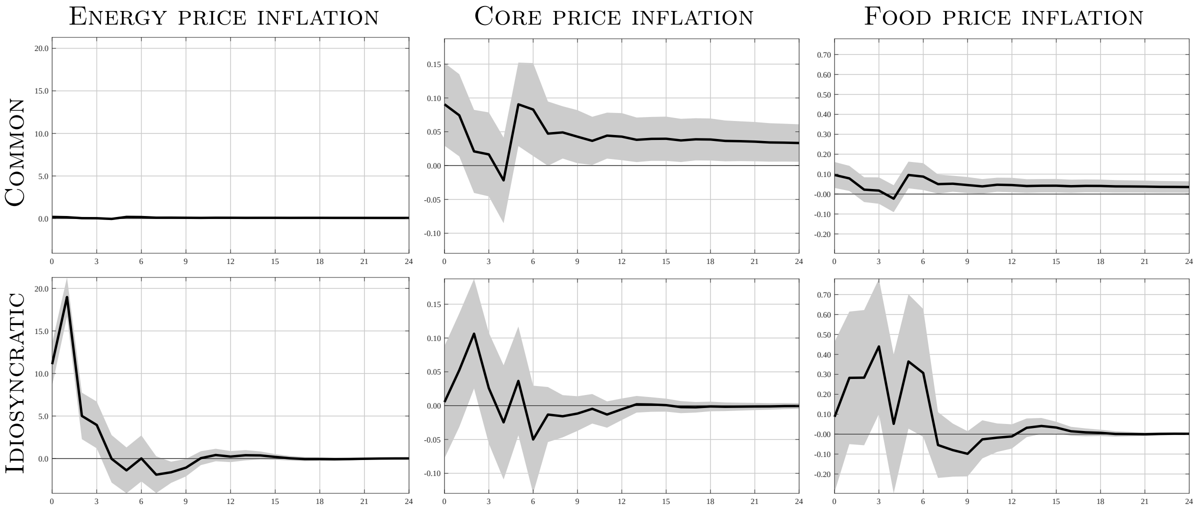
Notes: This figure shows the impulse response function to an oil price shock of the percentage change of the real (WTI) oil price (straight line with markers) with 90% confidence bands (shaded area). The x-axis represents months, while the y-axis represents percentage points.

The upper plots in Figure 3 show the estimated oil price pass-through into the common component of energy, core, and food PCE price inflation, while the lower plots show the pass-through into the idiosyncratic component.

As expected, the oil price passes through energy PCE price inflation almost entirely via the idiosyncratic component (left column). We estimate that an unexpected 10% increase in the real oil price increases energy prices of approximately 11% in the current month, 19% after one month, 5% after two months, and 4% after three months. The pass-through is completed in three months.

The middle column in Figure 3 shows the estimated oil-price pass-through into core PCE price inflation. The pass-through of an unexpected 10% increase in the real oil price into the idiosyncratic component of core prices is not significantly different from zero (lower plot), while the pass-through into the common component, despite being small, is very persistent: an unexpected 10% increase in the real oil price is estimated to increase core PCE price inflation for more than 4 years (not shown here). Although the pass-through into the idiosyncratic component is not statistically significant, for some of the components of core PCE—the more energy intensive ones—we estimate a positive and significant pass-through. However, these components account for a very small share of core PCE and therefore the aggregate effect turns out to be not statistically significant. This is the case, for example, of "Air transportation" that has a weight of $\frac{0.5}{100}$ in core PCE, and for which we estimate an increase of roughly four percent in the current month.

Figure 3: Oil price pass-through into US PCE price inflation:

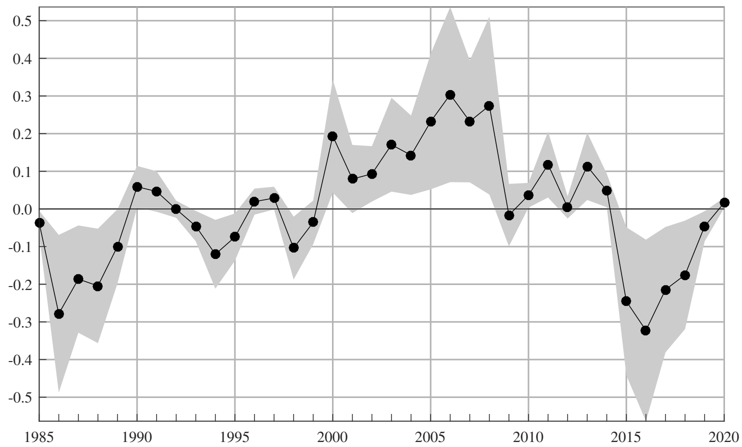


Notes: The upper plots show the pass-through of an unexpected 10% increase in the real oil price into the common component, while the lower plots show the pass-through into the idiosyncratic component. On each plot the black line is the point estimate, while the shaded area is the 90% confidence band. The x-axis represents months, while the y-axis represents percentage points.

The right column of Figure 3 shows the estimated oil price pass-through into food PCE price inflation. In line with at least one previous study, the estimated pass-through into the idiosyncratic component is not statistically different from zero (c.f. Baumeister and Kilian, 2014), while the pass-through via the common component is very similar to that for core PCE price inflation.

Finally, having estimated the pass-through from oil prices to PCE price inflation, we can calculate what the oil price contribution to core PCE price inflation was. Figure 4 shows the average contribution per year of changes in the oil price to core inflation up to 2020. We estimate that the plunge in the WTI spot prices from roughly \$100 per barrel to roughly $30 per barrel that occurred between July 2014 to February 2016 shaved-off a quarter of a percentage point from core PCE price inflation in 2015, and a third of a percentage point in 2016. We estimate that the drag from oil prices will persist in 2017 and 2018 (about two tenth each year), and that it will then disappear by 2020.

Figure 4: OIL PRICE CONTRIBUTION TO US CORE PCE PRICE INFLATION



Notes: This plot shows the average contribution per year of real oil price changes to US core PCE price inflation measured in percentage points (y-axis). The black line with markers is the point estimate while the shaded area is the 90% confidence band.

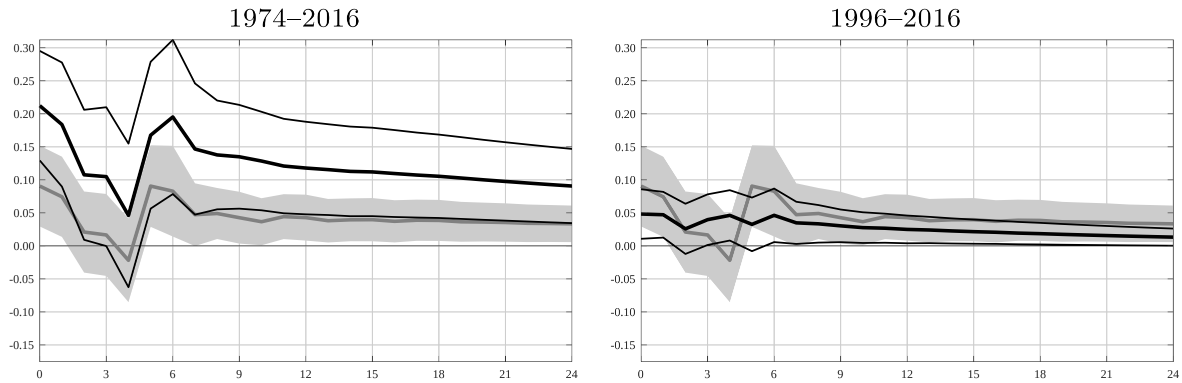
3.4 Has the oil price pass-through into core inflation changed over time?

There is extensive evidence that the oil price pass-through to core inflation has decreased over time (see Hooker, 2002; Chen, 2009, among others), with some authors finding that the pass-through has become negligible (Clark and Terry, 2010). Figure 5 shows the estimated pass-through into core PCE prices via the common component when the model is estimated on a longer sample starting in 1974 (left plot), and when the model is estimated on a shorter sample starting in 1996 (right plot). The choice of 1996 is for comparison with the euro area analysis performed in Section 4, while 1974 is the starting date of a large number of empirical analysis (for example Aastveit, 2014; Gao et al., 2014).

The results in Figure 5 confirm that the oil price pass–through into core inflation has decreased over time. In contrast with part of the literature (for example Clark and Terry, 2010) we still find a statistically significant pass-through even on the sample starting in 1996—the reason being that we disentangle between common and idiosyncratic movement in price fluctuations, thus not letting the noisy idiosyncratic component affect our estimation (see also the discussion in Section 3.5).

The literature has also asked why the pass-through has declined over time pointing to several (non mutually exclusive) explanations. For example, a possible explanation is that part of the decline in the pass-through can be attributed to the adoption of energy-saving technologies (Hooker, 2002; Bachmeier and Cha, 2011), while another explanation (Nordhaus, 2007; Bachmeier and Cha, 2011) points towards a change in the monetary policy response to oil price shocks (see Blinder and Rudd, 2013, for a review). While investigating properly the economic reasons of the decline in the pass-through into core inflation would require a structural model, here we provide some reduced form evidence.

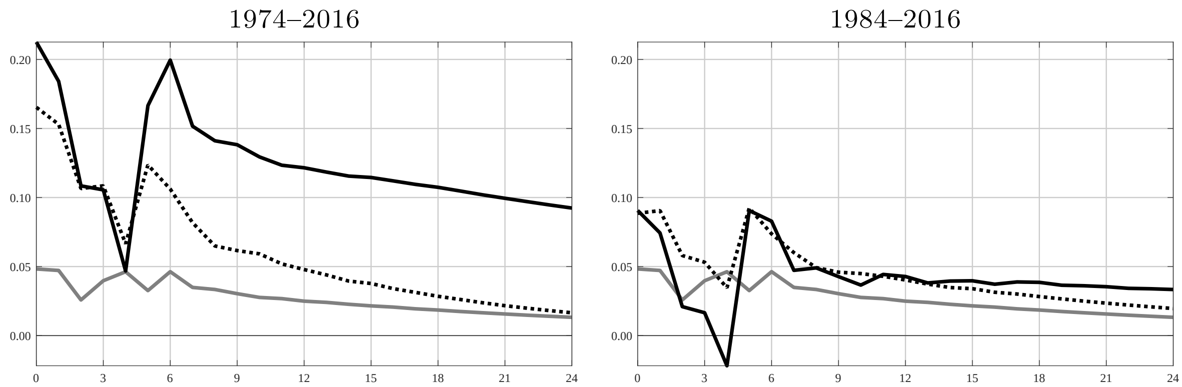
Figure 5: Has the oil price pass-through changed over time?



Notes: In each plot the gray line is the estimated pass-through in the benchmark model (the shaded area is the 90% confidence band), while the thick black line is the pass-through estimated on the sample starting in 1974 (left plot) or 1996 (right plot). The thin black lines are the 90 percent confidence bands for these alternative time periods. The x-axis represents months, while the y-axis represents percentage points.

Why does the oil price pass-through change when our model is estimated on different samples? To answer it is necessary first to notice that an alternative (and equivalent) way to estimate the oil price pass-through onto the common component of core inflation is to fit a bivariate VAR on the changes in the real oil price (y_t) and the common component of core inflation (χ_t^c).[6] Second, it is important to keep in mind that when we estimate the model in two different samples, we re-estimate the common factor and the factor loadings, and therefore χ_t^c. Indeed, had we not re-estimated χ_t^c, then the difference in the estimated pass-through would have been attributable to the mechanical fact that the coefficients of the VAR vary because they are estimated on two different samples. However, given that we re-estimate χ_t^c, the estimated coefficients of the VAR vary also because the estimated common component changes depending on the estimation sample. To disentangle between the contribution of common component estimation and contribution of the different VAR estimation, in Figure 6 we show the pass-through obtained when the VAR is estimated on the 1996-2016 sample while the common component is estimated on different periods.

Figure 6: WHY HAS THE OIL PRICE PASS-THROUGH CHANGED OVER TIME?



Notes: In each plot the black line is the estimated oil price pass-through into the common component of core inflation estimated on the 1974-2016 sample (left plot), and in the 1984-2016 benchmark sample (right plot). The dotted black line in the left (right) plot is the pass-through estimated when χ_t^c is estimated over the 1974-2016 (1984-2016) sample, but the VAR is estimated on the 1996-2016 sample. Finally, in both plots the gray line is the pass-through estimated on the 1996-2016 sample. The x-axis represents months, while the y-axis represents percentage points.

By looking at Figure 6 we can see that the magnitude of the estimated pass-through varies between samples mainly because of the common component estimation, whereas

[6] Let π_t^c be the monthly core prices inflation rate, then by using (1) and the aggregation weights we can write $\pi_t^c = \chi_t^c + \xi_t^c$, where $\chi_t^c = \sum_{i \in core} w_i \lambda_i f_t$, and $\xi_t^c = \sum_{i \in core} \xi_{it}$.

the persistence of the estimated pass-through varies between samples mainly because of the period used to estimate the VAR. The question then is why the common component estimated on different samples is different.

The answer is straightforward: the estimation of the common component depends on the comovement in the data, and the comovement in US disaggregate prices has changed over time. Indeed, the average percentage of disaggregate prices fluctuation explained by the common component has decreased from 18% in the 1974-2016 sample, to 8% in the 1984-2016 sample, to 6% in the 1996-2016 sample—at the aggregate level, the common component accounts for 90%, 57%, and 11% of core PCE fluctuations in the three samples, respectively.

In conclusion, our reduced form analysis points out that one of the reasons why the oil price pass-through onto core inflation has decreased over time is the fact that disaggregate prices have increasingly been driven by idiosyncratic dynamics.

3.5 Is our model miss-specified?

Our model assumes that the common component is driven by two shocks: a common shock, which has no structural interpretation, and an oil price shock. This is clearly a simplifying assumption as the common component might reflect the interplay of several different sources such as, for example, the Federal Reserve leaning against the inflationary pressure triggered by an oil price shock (Bernanke et al., 1997; Kilian and Lewis, 2011). Does this simplifying assumption bias our results? Are we making a mistake in not disentangling these different sources? This Section answers these questions.

In order to account for the interplay of different macroeconomic forces, we estimate a larger VAR model. In detail, we first estimate equation (1), and then, rather than estimating the VAR (2), we estimate a four–variable VAR including the percentage change in the real oil price (y_t), the unemployment rate, the Fed funds rate, and the common factor (f_t).[7]

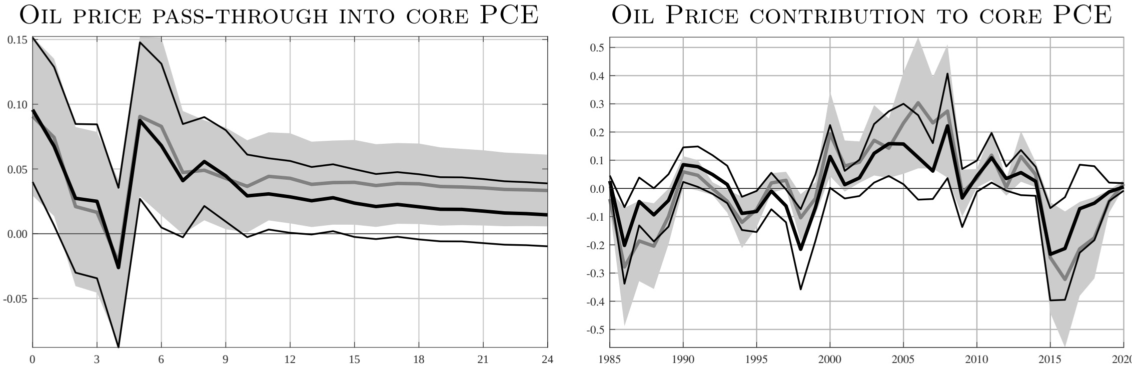
The left plot in Figure 7 compares the oil price pass-through into core inflation estimated with the larger VAR (black line) to that estimated with the benchmark model (gray line).[8] Results are essentially unchanged: the estimated pass-through with the enlarged VAR is just a touch smaller than the one estimated with the benchmark model, which is reflected in a smaller estimated oil price contribution to core inflation (right plot). In other words, the main conclusion of the paper is confirmed—the oil price pass-through to core inflation is small but statistically significant and long lasting.

The results in Figure 7 contrast with those in Clark and Terry (2010). Clark and Terry (2010), who estimate a time varying parameter VAR including core price inflation (π_t^c), energy price inflation, the unemployment rate, and the Fed funds rate, conclude that starting from 1985 the pass-through from energy price inflation to core price inflation is essentially zero. It can be shown that our model is very similar to that of Clark and Terry (2010) as it can be rewritten as a four–variable VAR including the percentage change in the real oil price, the unemployment rate, the Fed funds rate, and the common component of core price inflation (χ_t^c). Therefore, our conclusions are different from Clark and Terry (2010) because we include χ_t^c in lieu of π_t^c in the VAR model, that is we back-out the more noisy idiosyncratic component thus not letting it affect our estimation. This result further confirms the importance of disentangling between common and idiosyncratic movement in price fluctuations.

[7] The unemployment rate is the "Civilian Unemployment Rate: 16 yr +" from the Bureau of Labor Statistics, while the Fed Funds Rate is from the Federal Reserve Board. Both series where downloaded from Haver (LR@USECON, and FFED@USECON).

[8] When we estimate the larger VAR we do not impose the restriction in (4). Furthermore, the oil price shock is identified using a standard Choleski decomposition with the oil price ordered first.

Figure 7: Is our model miss-specified?



Notes: The left plot shows the pass-through of an unexpected 10% increase of the real oil price into the common component of core PCE prices. The gray line is the estimated pass-through in the benchmark model (the shaded area is the 90% confidence band), while the thick black line is the pass-through estimated using the enlarged VAR model (the thin black lines are the 90% confidence bands). The x-axis represents months, while the y-axis represents percentage points. The right plot shows the average contribution per year of real oil price to US core PCE price inflation measured in percentage points (y-axis). The gray line is the estimated contribution in the benchmark model (the shaded is the 90% confidence band), while the black line is the point estimate estimated using the enlarged VAR model (the thin black lines are the 90% confidence bands).

4 Oil price pass-through into inflation in the euro area

4.1 Data

The price data for the euro area are monthly Harmonized Indexes of Consumer Prices (HICP) (see Appendix A for details), while the weights are the official HICP item weights referred to 2016.[9] Both the disaggregate prices and the weights are available from Eurostat starting in 1996, and therefore the results for the euro area are obtained on a sample starting in 1996:M1, and ending in 2016:M6. Furthermore, given that Eurostat publishes seasonal adjusted series only for the aggregate indexes, we seasonally adjusted the disaggregated price series ourselves using X12 ARIMA.

HICP price indexes are available at 5-digit level Classification of Individual Consumption by Purpose (COICOP) for a total of 303 disaggregate prices, but for our analysis we consider disaggregated series at 3-digit level, which gives us a dataset of 95 series. From

[9] Weights of the Classification of Individual Consumption by Purpose (COICOP) categories are revised yearly and released in February together with the data for the month of January. In other words, while PCE weights change every month, HICP weights are constant within a given year.

this 95 price dataset we remove the following components that are available only starting from January 2000: “Dental services”, “Hospital services”, “Social protection”, “Other insurance”, “Insurance connected with health”, and “Medical and paramedical services”. The final dataset is composed of 87 price series covering 96.1% of the HICP index with 69% of the price indexes that have a weight smaller than $\frac{1}{100}$, and 14% of them that have a weight larger than $\frac{2}{100}$.

Finally, the oil price is measured by the Brent spot crude oil price, which is deflated by the HICP core price index. The data for the Brent price are taken from the US Energy Information Administration and the Wall Street Journal, and were downloaded from Haver (PEBRT@USECON), while the data for core HICP are taken from Eurostat (teicp200).

4.2 Common and idiosyncratic dynamics in HICP prices

Table 3 shows the percentage of variance explained by the first r factors. Similar to US PCE prices, EA HICP prices clearly admit a factor structure, but again it is unclear if more than one factor is needed. Moreover, the first factor accounts on average for roughly the same share of variance of disaggregate prices as in the US (see second and the third row of Table 3).[10]

Table 3: Common dynamics in EA HICP prices

r	1	2	3	4	5	6	7	8	9	10
μ_t^{EA}	9.8	4.2	3.9	3.6	3.0	2.9	2.6	2.5	2.3	2.3
μ_t^{US}	5.7	4.9	4.0	3.1	3.0	2.8	2.6	2.4	2.3	2.2

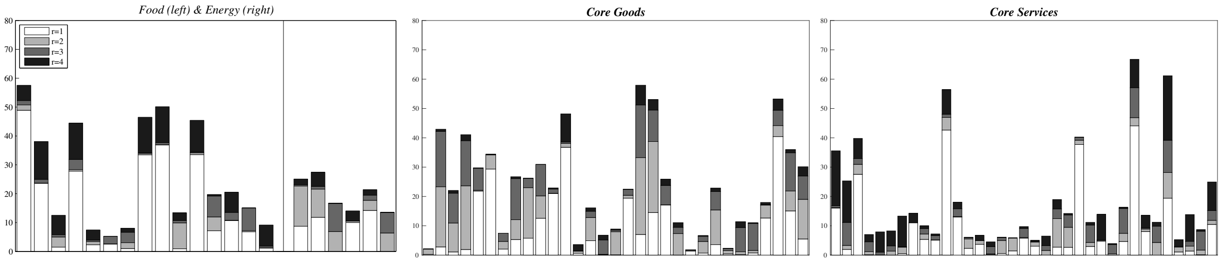
Notes: μ_r^{EA} is the percentages of total variance explained by the first r factors in the EA, while μ_r^{US} is the percentages of total variance explained by the first r factors in the US. Both μ_r^{EA} and μ_r^{US} were computed on a sample starting in 1996:M1 and ending in 2016:M6.

Figure 8 shows the percentage of variance of each variable explained by the first four factors, where we have divided the disaggregate prices into three plots each of which rep-

[10]Note also that in a model with one common factor, the common component accounts for 21% of core EA HICP inflation fluctuations. This is comparable to the shares estimated for US PCE prices on the 1996-2016 sample, which is 10%.

resents a different category. Although Figure 8 does not help in understanding how many factors to include in the model, it clearly shows that EA core services prices are more idiosyncratic than core goods. The uncertainty on the number of factors is not resolved by the Bai and Ng (2002) criteria that supports up to eight factors.

Figure 8: Common dynamics in EA HICP prices



Notes: This figure shows the percentage of variance (y-axis) of each variable (x-axis) explained by the first four factors. Each bar represent a different disaggregate price.

4.3 Oil price pass-through

In this Section we present estimates of the oil price pass-through into core EA HICP inflation, food EA HICP inflation, and energy EA HICP inflation. The benchmark specification is identical to the one used for US PCE prices, that is one factor ($r = 1$) and six lags in the VARs (2) and (3).

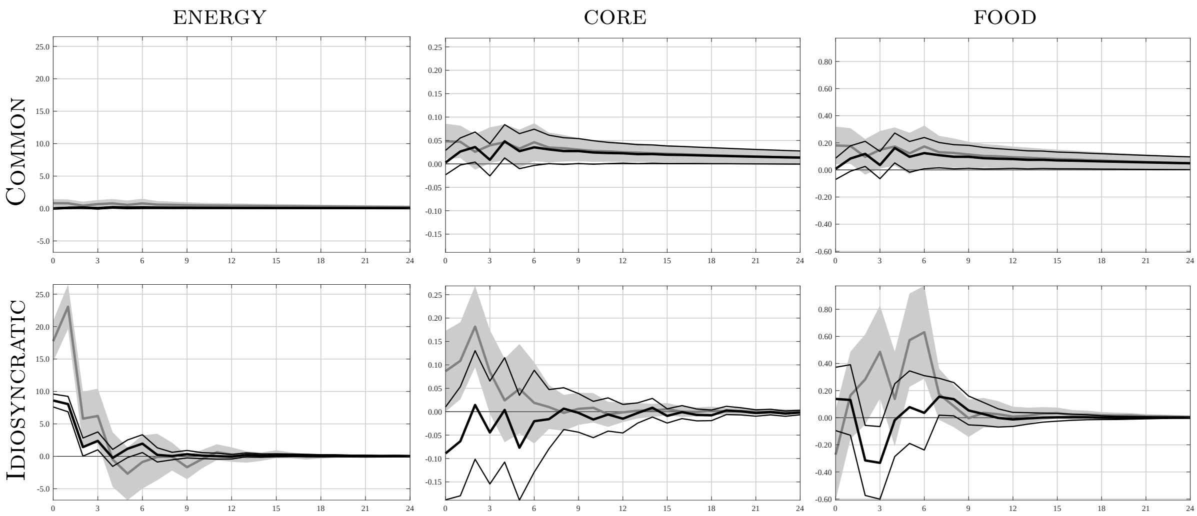
Figure 9 reports the estimated oil price pass-through into energy HICP inflation (left column), core HICP inflation (middle column), and food HICP inflation (right column), together with 90% bootstrap confidence bands.

An unexpected 10% increase in the real oil price increases energy prices of roughly 9% in the current month, of 8% after one month, of 1½ percent after two months, and of 2½ percent after three months. The pass-through is completed after three months. These numbers are considerably lower than those estimated for the US, most likely due to higher fuel taxes in the euro area. More precisely, in the euro area taxes on average account for roughly 60% of total gasoline prices, with crude oil prices accounting for roughly 20% (see

European Central Bank, 2011, page 87), while in the US the same shares are, respectively, 21% and 49% (source: EIA website `http://www.eia.gov/petroleum/gasdiesel/`).

The estimated pass-through into core HICP inflation in the EA is similar to that estimated for the US (middle column of Figure 9). The pass-through via the idiosyncratic component is not statistically different from zero, while the pass-through via the common component is null in the current month, but then small and persistent.

Figure 9: Oil price pass-through into EA HICP inflation

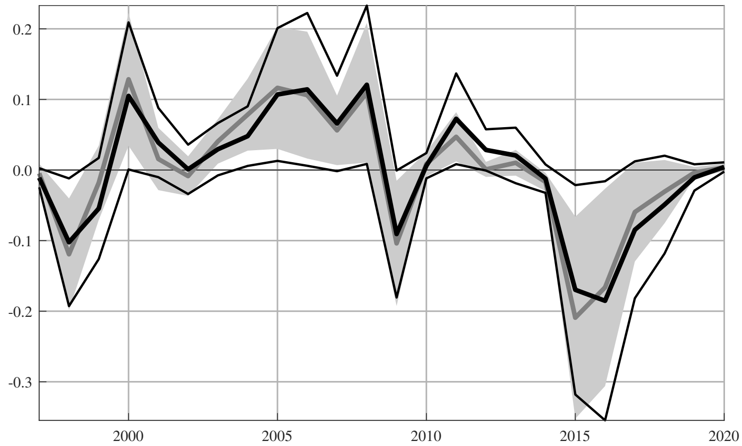


Notes: The upper plots show the pass-through of an unexpected 10% increase in the real oil price into the common component, while the lower plots show the pass-through into the idiosyncratic component. On each plot the thick black line is the point estimate for the EA, while the thin black lines are the 90% confidence bands. Likewise, the solid gray line and the shaded area are the point estimate and the confidence bands for the US, respectively. The x-axis represents months after the oil price increase, while the y-axis represents percentage points.

Figure 10 shows the oil price contribution to core EA HICP inflation up to 2020. We estimate that the plunge in the oil price shaved-off approximately 17 basis points to core inflation in the euro area in 2015, and 19 basis points in 2016. The drag from oil prices will persist in 2017 and 2018 (8 and 5 basis points), but it will fade away by 2019.[11] These numbers are very similar to those estimated for the US, with the effect being just slightly delayed.

[11] In a recent paper Conti et al. (2017) estimate that oil prices shaved off an average of (roughly) 13 basis points to EA core inflation. Such an estimate is lower but not statistically different than ours.

Figure 10: Oil price contribution to EA core HICP inflation



Notes: This plot shows the average contribution per year of real oil price to EA core HICP inflation measured in percentage points (y-axis). The thick black line is the point estimate for the EA while the thin black lines area are the 90% confidence bands). Likewise, the solid gray line and the shaded area are the point estimate and the confidence bands for the US, respectively.

5 Conclusions

In this paper we estimate the pass-through of oil price changes into consumer prices, both in the US and in the Euro area. To do so, we use a novel approach based on dynamic factor models and VARs, which allows us to distinguish between the specific (*idiosyncratic*) effect that oil price changes might have on individual disaggregate prices, from the macroeconomic (*common*) effect that oil price changes may have on all prices since they contribute to macroeconomic fluctuations.

Our results show that *common* and *idiosyncratic* dynamics in disaggregate prices have different statistical properties: *common* dynamics are slow moving, *idiosyncratic* dynamics fast moving and volatile. Disentangling these two components proves crucial when estimating the oil price pass-through into core inflation, as we estimate that the pass-through via the *idiosyncratic* component is essentially nil, while the pass-through via the *common* component is small, but non negligible, statistically different from zero and long lasting. This result is robust to estimation on different samples and with different model specifications.

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Appendix A Data

Appendix A.1 The US dataset

The price data for the US are monthly price indexes for personal consumption expenditures (PCE) by type of product. The data are taken from the NIPA Table 2.4.4U from the Bureau of Economic Analysis and downloaded from Haver. The data were seasonally adjusted by the Bureau of Economic Analysis, and large outliers—π_{it} is considered an outlier if its absolute value is larger than 10 times the interquantile range—were replaced by centered 9-month medians. In the table belows the column "ID" reports the position in the NIPA Table 2.4.4U, the column "share" reports the share of variance explained by the common component, while the column "weight" reports the weight of each component in the Total PCE index. The weight are those as of June 2016.

ID	Name	Label	share	weight
5	New motor vehicles	DNMVRX	22.0	2.09
10	Net purchases of used motor vehicles	DNPVRX	8.1	1.00
18	Motor vehicle parts and accessories	DMVPRX	15.7	0.53
22	Furniture and furnishings	DFFFRX	27.0	1.50
27	Household appliances	DAPPRX	20.0	0.39
30	Glassware, tableware, and household utensils	DUTERX	15.1	0.45
33	Tools and equipment for house and garden	DTOORX	10.0	0.18
37	Video, audio, photographic, and information processing equipment and media	DVAPRX	41.3	1.82
50	Sporting equipment, supplies, guns, and ammunition	DSPGRX	10.9	0.56
51	Sports and recreational vehicles	DWHLRX	7.0	0.41
58	Recreational books	DRBKRX	7.8	0.26
59	Musical instruments	DMSCRX	12.1	0.05
61	Jewelry and watches	DJRYRX	5.6	0.64
64	Therapeutic appliances and equipment	DTAERX	26.8	0.56
67	Educational books	DEBKRX	2.6	0.09
68	Luggage and similar personal items	DLUGRX	6.3	0.29
69	Telephone and facsimile equipment	DTCERX	21.7	0.14
74	Cereals and bakery products	DCBPRX	13.0	1.06
77	Meats and poultry	DMAPRX	0.2	1.18
82	Fish and seafood	DFISRX	4.8	0.10
83	Milk, dairy products, and eggs	DMDERX	2.2	0.65
87	Fats and oils	DFATRX	7.4	0.14
88	Fresh fruits and vegetables	DFAVRX	0.3	0.67
91	Processed fruits and vegetables	DPFVRX	10.4	0.22
92	Sugar and sweets	DSWERX	15.5	0.36
93	Food products, not elsewhere classified	DOFDRX	30.4	1.07
94	Nonalcoholic beverages purchased for off-premises consumption	DNBVRX	16.6	0.70
97	Alcoholic beverages purchased for off-premises consumption	DAOPRX	22.3	1.08
101	Food produced and consumed on farms	DFFDRX	0.1	0.005
103	Garments	DGARRX	8.7	2.39
107	Other clothing materials and footwear	DOCCRX	9.4	0.65
112	Motor vehicle fuels, lubricants, and fluids	DMFLRX	2.0	1.98
115	Fuel oil and other fuels	DFULRX	3.0	0.15
119	Pharmaceutical and other medical products	DPHMRX	24.7	3.82
124	Recreational items	DREIRX	27.4	1.28
129	Household supplies	DHOURX	36.0	1.01
135	Personal care products	DOPCRX	24.5	1.04
139	Tobacco	DTOBRX	1.5	0.85
140	Magazines, newspapers, and stationery	DNEWRX	24.2	0.78

ID	Name	Label	share	weight
152	Rental of tenant-occupied nonfarm housing	DTENRX	41.7	4.02
156	Imputed rental of owner-occupied nonfarm housing	DOWNRX	40.5	11.54
159	Rental value of farm dwellings	DFARRX	0.0	0.16
160	Group housing	DGRHRX	33.3	0.01
163	Water supply and sewage maintenance	DWSMRX	11.8	0.58
164	Garbage and trash collection	DREFRX	20.7	0.14
166	Electricity	DELCRX	18.6	1.42
167	Natural gas	DGHERX	5.2	0.39
170	Physician services	DPHYRX	49.2	4.06
171	Dental services	DDENRX	32.3	0.98
172	Paramedical services	DPMSRX	38.8	2.74
179	Hospitals	DHSPRX	45.8	8.00
183	Nursing homes	DNRSRX	20.8	1.46
187	Motor vehicle services	DMVSRX	52.4	2.14
196	Ground transportation	DGRDRX	9.0	0.35
203	Air transportation	DAITRX	2.4	0.43
204	Water transportation	DWATRX	6.9	0.03
206	Membership clubs, sports centers, parks, theaters, and museums	DRLSRX	13.8	1.46
214	Audio-video, photographic, and information processing equipment services	DAVPRX	7.0	0.80
220	Gambling	DGAMRX	50.1	1.02
224	Other recreational services	DOTRRX	19.1	0.46
231	Meals and nonalcoholic beverages	DMABRX	65.7	4.83
239	Alcohol in purchased meals	DAPMRX	21.8	0.72
240	Food furnished to employees (including military)	DFOORX	23.4	0.16
243	Accommodations	DACCRX	7.7	0.96
248	Financial services furnished without payment	DIMPRX	2.6	2.59
252	Financial service charges, fees, and commissions	DOFIRX	4.0	2.05
265	Life insurance	DLIFRX	21.9	0.71
266	Net household insurance	DFINRX	0.0	0.10
269	Net health insurance	DHINRX	0.9	1.47
273	Net motor vehicle and other transportation insurance	DTINRX	0.2	0.54
276	Telecommunication services	DTCSRX	6.2	1.29
280	Postal and delivery services	DPSSRX	3.5	0.08
285	Higher education	DHEDRX	8.6	1.49
288	Nursery, elementary, and secondary schools	DNEHRX	16.5	0.35
291	Commercial and vocational schools	DVEDRX	8.7	0.43
293	Legal services	DGALRX	17.9	0.84
294	Accounting and other business services	DPRORX	12.4	0.27
298	Labor organization dues	DUNSRX	27.4	0.11
299	Professional association dues	DAXSRX	18.0	0.07
300	Funeral and burial services	DFUNRX	24.5	0.22
302	Personal care services	DPCSRX	42.8	1.12
305	Clothing and footwear services	DCFSRX	49.8	0.14
310	Child care	DCHCRX	8.0	0.29
311	Social assistance	DSCWRX	16.3	0.91
318	Social advocacy and civic and social organizations	DSADRX	18.9	0.13
319	Religious organizations' services to households	DRELRX	5.8	0.05
320	Foundations and grantmaking and giving services to households	DGIVRX	14.1	0.01
321	Household maintenance	DHHMRX	23.1	0.63
339	Final consumption expenditures of NPISH	DNPIRX	2.9	2.72

Appendix A.2 The euro area dataset

The price data for the euro area are monthly price indexes for Harmonized Indexes of Consumer Prices (HICP) by type of product taken from the Eurostat website `http://appsso.eurostat.ec.europa.eu/nui/show.do?dataset=prc_hicp_midx&lang=en`. The data were seasonally adjusted by using the X-12-ARIMA seasonal adjustment method, and large outliers—π_{it} is considered an outlier if its absolute value is larger than 10 times the interquantile range—were replaced by centered 9-month medians. In the table belows the column "share" reports the share of variance explained by the common component, while the column "weight" reports the weight of each component in the Total HICP index. The weight are those as of 2016.

Name	Label	share	weight
Bread and cereals	CP0111	48.1	2.6
Meat	CP0112	28.2	3.5
Fish and seafood	CP0113	2.6	1.0
Milk, cheese and eggs	CP0114	27.4	2.1
Oils and fats	CP0115	0.7	0.4
Fruit	CP0116	2.7	1.2
Vegetables	CP0117	1.4	1.7
Sugar, jam, honey, chocolate and confectionery	CP0118	31.5	1.0
Food products n.e.c.	CP0119	36.9	0.5
Coffee, tea and cocoa	CP0121	3.1	0.4
Mineral waters, soft drinks, fruit and vegetable juices	CP0122	29.5	0.9
Spirits	CP0211	5.6	0.4
Wine	CP0212	9.9	0.8
Beer	CP0213	4.5	0.6
Tobacco	CP022	2.4	2.4
Clothing materials	CP0311	0.2	0.0
Garments	CP0312	2.4	4.4
Other articles of clothing and clothing accessories	CP0313	0.6	0.3
Cleaning, repair and hire of clothing	CP0314	17.6	0.2
Shoes and other footwear	CP0321-322	1.9	1.2
Actual rentals paid by tenants	CP0411-412	5.0	6.5
Materials for the maintenance and repair of the dwelling	CP0431	21.2	0.4
Services for the maintenance and repair of the dwelling	CP0432	31.1	0.9
Water supply	CP0441	0.0	0.6
Refuse collection	CP0442	0.9	0.6
Sewerage collection	CP0443	1.1	0.6
Other services relating to the dwelling n.e.c.	CP0444	1.4	0.9
Electricity	CP0451	7.7	2.7
Gas	CP0452	11.9	1.9
Liquid fuels	CP0453	0.2	0.6
Solid fuels	CP0454	10.2	0.2
Heat energy	CP0455	15.0	0.2
Furniture and furnishings	CP0511	30.4	1.9
Carpets and other floor coverings	CP0512	2.8	0.2
Repair of furniture, furnishings and floor coverings	CP0513	12.1	0.1
Household textiles	CP0520	5.5	0.4
Major household appliances whether electric or not	CP0531-532	5.8	0.9
Repair of household appliances	CP0533	10.6	0.1
Glassware, tableware and household utensils	CP0540	10.2	0.5
Major tools and equip. and small tools and misc. accessories	CP0551-552	20.8	0.5

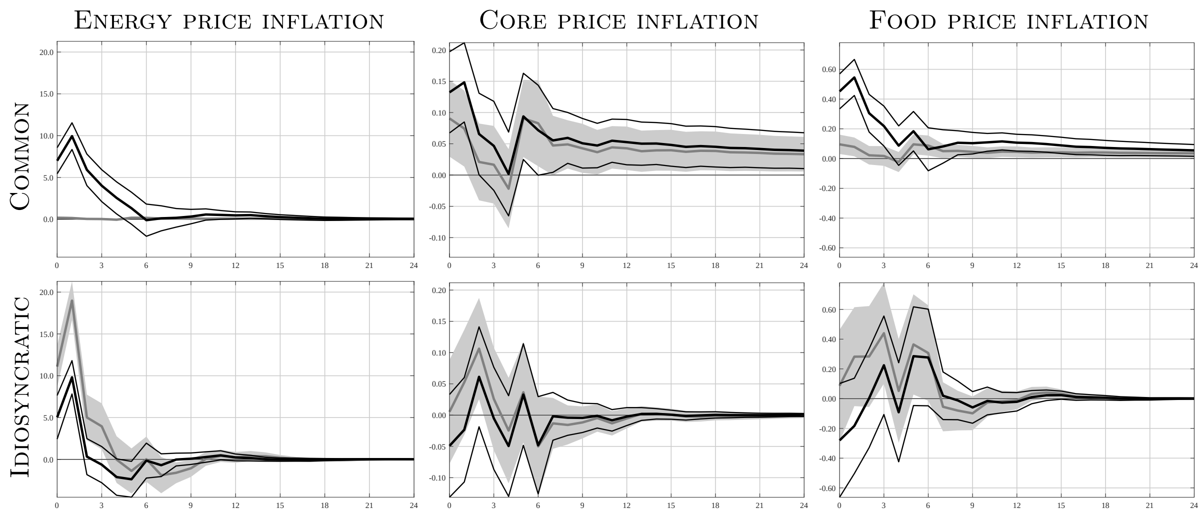
Name	Label	share	weight
Non-durable household goods	CP0561	35.9	1.0
Domestic services and household services	CP0562	8.6	0.9
Pharmaceutical products	CP0611	0.0	1.3
Other medical products, therapeutic appliances and equipment	CP0612-613	6.0	0.8
Motor cars	CP0711	0.3	3.5
Motor cycles, bicycles and animal drawn vehicles	CP0712-714	0.1	0.3
Spare parts and accessories for personal transport equipment	CP0721	17.9	0.6
Fuels and lubricants for personal transport equipment	CP0722	0.3	4.2
Maintenance and repair of personal transport equipment	CP0723	42.2	2.5
Other services in respect of personal transport equipment	CP0724	12.2	1.2
Passenger transport by railway	CP0731	2.2	0.6
Passenger transport by road	CP0732	4.0	0.6
Passenger transport by air	CP0733	0.6	0.7
Passenger transport by sea and inland waterway	CP0734	0.5	0.1
Combined passenger transport	CP0735	1.8	0.6
Other purchased transport services	CP0736	6.2	0.1
Postal services	CP081	4.3	0.2
Telephone and telefax equipment	CP0820-830	0.2	3.0
Equipment for the reception, recording and reproduction of sound and picture	CP0911	5.8	0.4
Photographic and cinematographic equipment and optical instruments	CP0912	14.8	0.1
Information processing equipment	CP0913	19.4	0.5
Recording media	CP0914	0.0	0.2
Repair of audio-visual, photographic and information processing equipment	CP0915	5.3	0.1
Major durables for outdoor recreation and indoor recreation	CP0921-922	1.0	0.3
Maintenance and repair of other major durables for recreation and culture	CP0923	1.4	0.0
Games, toys and hobbies	CP0931	1.6	0.6
Equipment for sport, camping and open-air recreation	CP0932	2.8	0.3
Gardens, plants and flowers	CP0933	0.6	0.6
Pets and related products; veterinary and other services for pets	CP0934-935	37.7	0.7
Recreational and sporting services	CP0941	6.6	0.9
Cultural services	CP0942	6.7	1.4
Books	CP0951	0.0	0.5
Newspapers and periodicals	CP0952	0.2	0.7
Miscellaneous printed matter;stationery and drawing materials	CP0953-954	11.0	0.3
Package holidays	CP096	0.1	1.7
Pre-primary, primary, second., etc, and educ. not def. by level	CP10X0	7.5	1.1
Restaurants, cafés and the like	CP1111	48.2	7.1
Canteens	CP1112	6.6	0.7
Accommodation services	CP112	0.0	1.8
Hairdressing salons and personal grooming establishments	CP1211	25.7	1.2
Electrical appliances for personal care; other appliances, articles and products for personal care	CP1212-1213	46.5	1.7
Jewellery, clocks and watches	CP1231	11.9	0.5
Other personal effects	CP1232	5.7	0.5
Insurance connected with the dwelling	CP1252	0.5	0.3
Insurance connected with transport	CP1254	1.1	0.8
Other financial services n.e.c.	CP12622	0.5	0.6
Other services n.e.c.	CP127	14.8	1.1

Appendix B Robustness

In this section we provide robustness checks for the US.

As explained in Section 3.2 there is considerable uncertainty on the number of factors to be included in the model, and in the first robustness check we show results with a larger number of factors included. Figure B1 reports results when $r = 3$ as in Reis and Watson (2010). In a nutshell: results do change in that, although the sum of the point estimates of common and idiosyncratic pass-through does not change, the composition between the two components slightly does. For example, in the model with one factor an unexpected 10% increase in the real oil price pass-through via the idiosyncratic component increases PCE energy by 11.1% in the current month, while the (point-estimate) pass-through via the common component is 0.2%. In the model with three factors an unexpected 10% real oil price increase pass-through via the idiosyncratic component increases PCE energy by 5%, while the pass-through via the common component is 7%.

Figure B1: Robustness analysis with respect to number of factors
Oil price pass-through into US PCE price inflation



Notes: The upper plots show the pass-through of an unexpected 10% increase in the real oil price into the common component, while the lower plots show the pass-through into idiosyncratic component. On each plot the gray line is the estimated pass-through in the benchmark model (the shaded area is the 90% confidence band), while the black line is is the pass-through estimated when $r = 3$ (the dashed black lines are the 90% confidence bands). The x-axis represents months, while the y-axis represents percentage points.

The second check is done with respect to the structure of the model. As explained in Section 2 our model is very similar to a standard FAVAR model (Bernanke et al., 2005). In our model, the oil price is expected to have not only a common effect on all prices, but also to possibly have an idiosyncratic effect on energy intensive items. In a FAVAR model, instead, the oil price is treated as an observed factor, which means that the oil price is part of the common space only, and it has no effects on the idiosyncratic component. In formulas, equation (1) is replaced by

$$\pi_{it} = \boldsymbol{\lambda}_i' \mathbf{f}_t + \gamma_i y_t + \xi_{it} \tag{B1}$$

while (2) remains equal and the idiosyncratic component is not modeled. By substituting (2) into (B1) we can derive the oil price pass-through into the inflation rate of price i implied by the FAVAR as:

$$\tilde{\psi}_i(L) = \boldsymbol{\lambda}_i' \mathbf{c}_{i12}(L) + \gamma_i c_{i22}(L). \tag{B2}$$

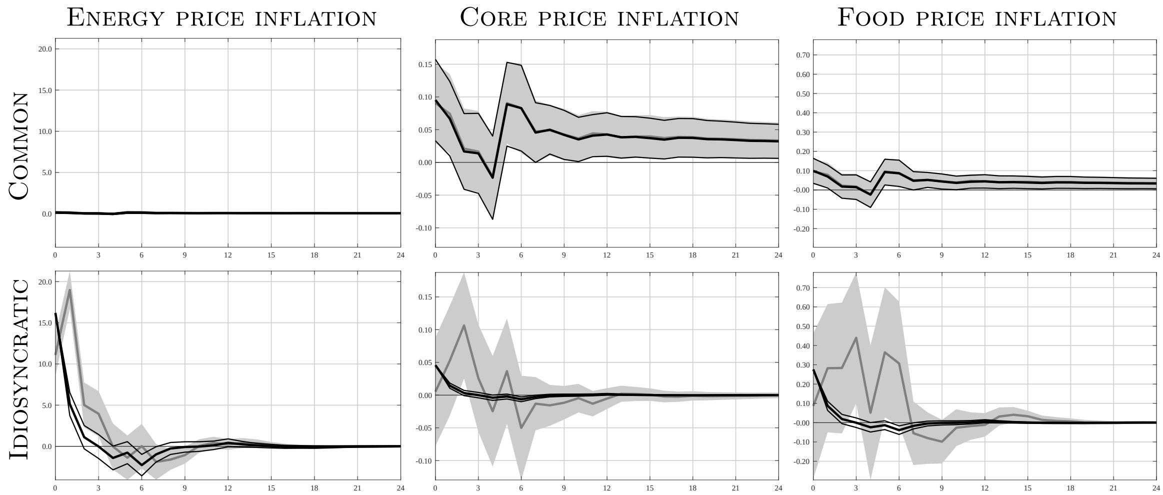
Now, in principle $\tilde{\psi}_i(L)$ should be equal to $\tilde{\psi}_i^{\chi}(L)$, and $\tilde{\psi}_i^{\xi}(L)$ should be zero, as in a FAVAR model the oil price is treated as an observed factor. However, with a clear and acknowledged abuse of notation, we are going to write $\tilde{\psi}_i^{\chi}(L) = \boldsymbol{\lambda}_i \mathbf{c}_{i12}(L)$ and $\tilde{\psi}_i^{\xi}(L) = \gamma_i c_{i22}(L)$, and then by comparing (B2) with (5) we can see that $\tilde{\psi}_i^{\chi}(L) = \psi_i^{\chi}(L)$, and $\tilde{\psi}_i^{\xi}(L) \neq \psi_i^{\xi}(L)$.

Figure B2 compares our benchmark estimated oil price pass-through with the one estimated using a FAVAR.[12] More precisely, the top row of Figure B2 shows the pass-through into the common component, while the bottom row shows the pass-through into the idiosyncratic component. As expected, the estimated pass-through into the common component

[12]The FAVAR is estimated using PCA and OLS. More specifically, we follow Boivin et al. (2009) and Aastveit (2014) and we first estimate $\mathbf{f}_t$ by PCA, call it $\widehat{\mathbf{f}}_t^0$, and then we iterate between (1) estimate $\boldsymbol{\lambda}_i$ and γ_i by regressing x_{it} into $\widehat{\mathbf{f}}_t^{j-1}$ and y_t, and (2) estimate $\widehat{\mathbf{f}}_t^j$ by PCA on $\tilde{\mathbf{x}}_t = \mathbf{x}_t - \widehat{\boldsymbol{\gamma}}^j y_t$. Alternatively a FAVAR could be estimated in one shot either by estimating a restricted DFM with Maximum Likelihood as in Juvenal and Petrella (2015) and Luciani (2015), or with Bayesian method as in Bernanke et al. (2005).

is identical, while the estimated idiosyncratic pass-through is similar. All in all, the results in Figure B2 show that had we estimated a standard FAVAR rather than the model in Section 2 we would have reached the same conclusions.

Figure B2: ROBUSTNESS ANALYSIS WITH RESPECT TO MODEL STRUCTURE
OIL PRICE PASS-THROUGH INTO US PCE PRICE INFLATION



Notes: The upper plots show the pass-through of an unexpected 10% increase in the real oil price into the common component ($\boldsymbol{\lambda}_i'\mathbf{c}_{i12}(L)$), while the lower plots show the pass-through into idiosyncratic component ($d_{i12}(L)$ for the benchmark model, and $\gamma_i c_{i22}(L)$ for the FAVAR). On each plot the gray line is the estimated pass-through in the benchmark model (the shaded area is the 90% confidence band), while the black line is the pass-through estimated with the FAVAR (the dashed black lines are the 90% confidence bands). The x-axis represents months, while the y-axis represents percentage points.