SVAR-based supply and demand decomposition of inflation

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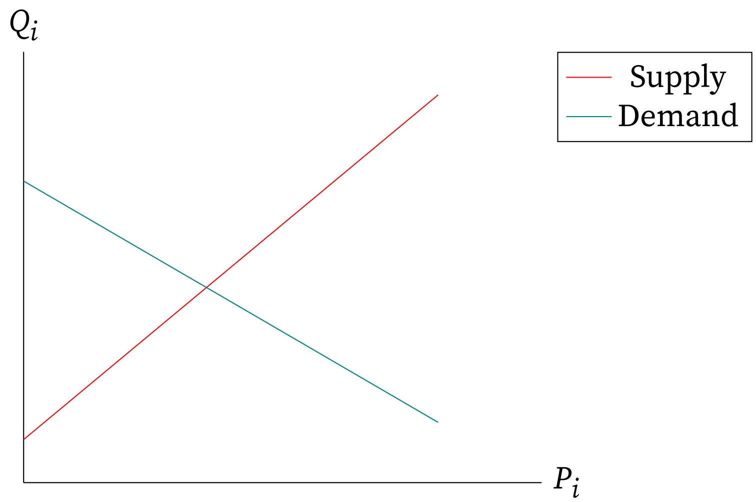
1. Methodology and Data

1.1. Basis of *Shapiro (2022)*

The methodology proposed by Adam Hale Shapiro in his 2022 paper "Decomposing Supply and Demand Driven Inflation"(1) takes its foundations in the work of Jump and Kohler (2022)(2). The core assumption of the framework is that for each sector/section (i) of the inflation breakdown, an upward sloping in price supply curve and a downward demand curve can be assumed.



In theory, assuming $\sigma_i > 0$ and $\delta_i > 0$, we have:

$$\begin{aligned} \text{Supply :} \quad & Q_i = \sigma_i.P_i + \alpha_i \\ \text{Demand :} \quad & P_i = -\delta_i.Q_i + \beta_i \end{aligned}$$

Shocks are then defined as vertical movements of the curves :

$$\begin{aligned} \text{Supply shock : } \varepsilon_t^s = \Delta\alpha_i \quad &= (Q_{i,t} - \sigma_i P_{i,t}) - (Q_{i,t-1} - \sigma_i P_{i,t-1}) \\ \rightarrow \varepsilon_t^s &= \Delta Q_{i,t} - \sigma_i \Delta P_{i,t} \\ \text{Demand shock : } \varepsilon_t^d = \Delta\beta_i \quad &= (P_{i,t} + \delta_i Q_{i,t}) - (P_{i,t-1} + \delta_i Q_{i,t-1}) \\ \rightarrow \varepsilon_t^d &= \Delta P_{i,t} + \delta_i \Delta Q_{i,t} \end{aligned}$$

We can easily show that the two previous equations lead to :

$$\begin{cases} \Delta Q_{i,t} & = \frac{1}{1+\delta_i}(\varepsilon_t^s + \sigma_i.\varepsilon_t^d) \\ \Delta P_{i,t} & = \frac{1}{\sigma_i(1+\delta_i)}(\sigma_i.\varepsilon_t^d - \delta_i.\varepsilon_t^s) \end{cases}$$

As we assume $\sigma_i > 0$ and $\delta_i > 0$, we can derive expected comovements between the two variables following supply and demand shocks.

$$\begin{cases} \text{Supply shock } \ \varepsilon^s > 0 & : \Delta^+ Q \quad \& \quad \Delta^- P > \text{Negative comovements (S)} \\ \text{Demand shock } \ \varepsilon^d > 0 & : \Delta^+ Q \quad \& \quad \Delta^+ P > \text{Positive comovements (D)} \end{cases}$$

Consider the following structural VAR of (arbitrary) order p (dropping i indices). Let $z_t = \begin{bmatrix} \Delta Q_t \\ \Delta P_t \end{bmatrix}$ and the structural shocks $\varepsilon_t = \begin{bmatrix} \varepsilon_t^s \\ \varepsilon_t^d \end{bmatrix}$:

$$A. \begin{bmatrix} \Delta Q_t \\ \Delta P_t \end{bmatrix} = \mu + \sum_{i=1}^{p} A_i.z_{t-i} + \begin{bmatrix} \varepsilon_t^s \\ \varepsilon_t^d \end{bmatrix}$$

With ν_t the residuals of the estimated reduced-form VAR(p) we should have $\nu_t = A^{-1}.\varepsilon_t$
Let A satisfy $A \equiv \begin{pmatrix} 1 & -\alpha \\ \beta & 1 \end{pmatrix}$ with $\alpha, \beta > 0$, it follows that $A^{-1} = \frac{1}{1+\alpha\beta}\begin{pmatrix} 1 & \alpha \\ -\beta & 1 \end{pmatrix}$
Omitting the t indices we have :

$$\begin{bmatrix} \nu^s \\ \nu^d \end{bmatrix} = A^{-1}. \begin{bmatrix} \varepsilon^s \\ \varepsilon^d \end{bmatrix}$$

$$\begin{bmatrix} \nu^s \\ \nu^d \end{bmatrix} = \frac{1}{1+\alpha\beta}\begin{pmatrix} 1 & \alpha \\ -\beta & 1 \end{pmatrix}\begin{bmatrix} \varepsilon^s \\ \varepsilon^d \end{bmatrix}$$

As $\frac{1}{1+\alpha\beta} > 0$, we finally have:

$$\begin{cases} \nu^s & \propto \varepsilon^s + \alpha.\varepsilon^d \\ \nu^d & \propto -\beta.\varepsilon^s + \varepsilon^d \end{cases}$$

Which leads to:

$$\begin{cases} \varepsilon^s > 0\,,\ \varepsilon^d > 0 & \Rightarrow \nu^s > 0 \\ \varepsilon^s < 0\,,\ \varepsilon^d < 0 & \Rightarrow \nu^s < 0 \\ \varepsilon^s < 0\,,\ \varepsilon^d > 0 & \Rightarrow \nu^d > 0 \\ \varepsilon^s > 0\,,\ \varepsilon^d < 0 & \Rightarrow \nu^d < 0 \end{cases}$$

Looking at the signs of ν^s and ν^d we can then back-track and derive the signs of ε^s and ε^d. For example when $\nu^s > 0$ and $\nu^d < 0$ we have $\varepsilon^s > 0$. We derive:

$$\begin{cases} \nu^s > 0,\ \nu^d < 0 \Rightarrow \varepsilon^s > 0 & \text{+ Supply shock} \quad (1) \\ \nu^s < 0,\ \nu^d > 0 \Rightarrow \varepsilon^s < 0 & \text{- Supply shock} \quad (2) \\ \nu^s > 0,\ \nu^d > 0 \Rightarrow \varepsilon^d > 0 & \text{+ Demand shock} \quad (3) \\ \nu^s < 0,\ \nu^d < 0 \Rightarrow \varepsilon^d < 0 & \text{- Demand shock} \quad (4) \end{cases}$$

Thus, from (1) and (2) we see that reduced-form errors of opposite sign (negative comovements of P and Q) are associated with demand shocks, which is consistent with theory (S). Similarly, from (3) and (4) reduced-form errors of the same sign (positive comovements of P and Q) are associated with demand shocks, again consistent with theory (D).

Hence, assuming that A in the structural VAR is of the form $\begin{pmatrix} 1 & -\alpha \\ \beta & 1 \end{pmatrix}$ with $\alpha, \beta > 0$, or more generally $A = \begin{pmatrix} a_{11} > 0 & a_{12} < 0 \\ a_{21} > 0 & a_{22} > 0 \end{pmatrix}$, thus **ensures** that expected structural shocks' effects on the covariates derived from theory are consistent in the model. We can then infer aforementioned effects from the reduced-form residuals that are in practice derived from the estimation of a VAR(p) model.

1.2. Proxy for European countries

In the original paper from Shapiro the data used are price, quantity and expenditures from the personal consumption expenditure (PCE) data with fourth level of disaggregation of the Bureau of Economic Analysis (BEA). However it is more complicated when considering European countries. Indeed, similar quantity series are not readily available for each of the 4-digit COICOP classification component of the HICP.

To tackle this issue, we follow the indication provided by Eduardo Goncalves and Gerrit Koester in the ECB Economic Bulletin 7 of 2022(3). We consider the turnover series from the short-term statistics data of the ECB as proxy for demand, and once deflated as proxy for the quantity series. The main issue that remains is that the classification of sectors in the HICP (COICOP) is different from the classification of sectors used in the short-term statistics data (NACE Rev.2). We then try to match as best as possible each COICOP sector to a NACE Rev.2 counterpart. Out of the 94 4-digit COICOP sectors, we managed to create 75 pairs. On average that is around 80% of the overall HICP that has been matched. In what follows we refer for each sector the 'quantity index' as the real matched turnover series (CPI deflated). The sectors that have not been matched will thus make up the *unclassified* part of total inflation in the proposed charts.

2. Literature review and discussion

2.1. Classification from *Shapiro (2022)*

2.1.1. Baseline classification

With our price-quantity pairs matched for 75 sectors, we run the following monthly VAR for each of the sectors denoted by index (i). We did so in Python using the *statsmodels* library, which we also used later on for ADF tests and lag selections:

$$\begin{bmatrix} \Delta q_{i,t} \\ \Delta p_{i,t} \end{bmatrix} = \sum_{j=1}^{p} A_j \cdot \begin{bmatrix} \Delta q_{i,t-j} \\ \Delta p_{i,t-j} \end{bmatrix} + \begin{bmatrix} \nu_{i,t}^{q} \\ \nu_{i,t}^{p} \end{bmatrix}$$

Where $\Delta q_{i,t}$ and $\Delta p_{i,t}$ are the demeaned first-difference of the log-transformed quantity and price indices ($x_{i,t} = \log(X_{i,t})$). This assumes $\Delta q_{i,t}$ and $\Delta p_{i,t}$ are second-order stationary, which seems to be the case.

We ran multiple tests to check whether the stationarity assumption holds. We ran augmented Dickey-Fuller tests on both our price and quantity series: the null hypothesis is rejected for 63% of the differenced log price series and 96% of the differenced log quantity series at the 5% level (respectively 47% and 94% at the 1% level). We thus consider this hypothesis to be reasonable. We also checked for non-log series stationarity as well as linear and quadratric trend stationarity without obtaining more compelling results 5.1.

In our implementation of the methodology, we let the order p of the VAR be automatically selected via minimisation of a statistical criterion (AIC or BIC) for each sector instead of imposing $p = 12$ as done by Shapiro. Even though he explains the classification seems to be robust to the lag order selection we would rather let it be sector-specific than adding another constraint on the methodology.

Note that we said 75 sectors had matched proxy quantity series, but we cannot run 75 VAR. Indeed, even though we managed to match the series we still had some data missing in the series themselves. Thus, for each zone in our study (France, Germany, Spain and EU27) we flag sectors that have data problems for either the price or quantity series. A sector being flagged mainly stems from the latest data available being earlier than 2023 (some stop in 2022 or 2020 and some even in 2015). Overall we run regressions on 52 (EU27) to 72 (France) sectors.

The estimated reduced-form residuals (ν_t^q, ν_t^p) (equivalent to (ν_t^s, ν_t^d) in the previous section) are then used to label each month (t) for each sector (i) using the following rule

$$\mathbb{1}_{i,sup(+)}(t) = \begin{cases} 1 & \text{if } \nu_{i,t}^q > 0, \nu_{i,t}^p < 0 \\ 0 & \text{otherwise} \end{cases}$$

$$\mathbb{1}_{i,sup(-)}(t) = \begin{cases} 1 & \text{if } \nu_{i,t}^q < 0, \nu_{i,t}^p > 0 \\ 0 & \text{otherwise} \end{cases}$$

$$\mathbb{1}_{i,dem(+)}(t) = \begin{cases} 1 & \text{if } \nu_{i,t}^q > 0, \nu_{i,t}^p > 0 \\ 0 & \text{otherwise} \end{cases}$$

$$\mathbb{1}_{i,dem(-)}(t) = \begin{cases} 1 & \text{if } \nu_{i,t}^q < 0, \nu_{i,t}^p < 0 \\ 0 & \text{otherwise} \end{cases}$$

$$\Rightarrow \mathbb{1}_{i,sup}(t) = \mathbb{1}_{i,sup(+)}(t) + \mathbb{1}_{i,sup(-)}(t) \tag{1}$$

$$\Rightarrow \mathbb{1}_{i,dem}(t) = \mathbb{1}_{i,dem(+)}(t) + \mathbb{1}_{i,dem(-)}(t) \tag{2}$$

From now on, at date t experiencing a demand shock or being demand-driven or being labeled demand-driven all mean that $\mathbb{1}_{i,dem}(t) = 1$ *(vice versa with supply).*

It follows that each month, overall month-over-month inflation $\pi_{t,t-1}$ can be divided into supply and demand driven components. As the overall CPI is a weighted average of its sectorial inflation $\pi_{i,t,t-1}$ we denote $\omega_{i,y}$ the weight of sector (i) at year y in the CPI. In the following equation y_t means the year of month t.

$$\pi_{t,t-1} = \sum_i \mathbb{1}_{i,sup}(t)\omega_{i,y_t}\pi_{i,t,t-1} + \sum_i \mathbb{1}_{i,dem}(t)\omega_{i,y_t}\pi_{i,t,t-1}$$
$$\pi_{t,t-1} = \pi_{t,t-1}^{sup} + \pi_{t,t-1}^{dem}$$

We present results for year-over-year inflation, which is simply given by:

$$\begin{cases} \pi_{t,t-12}^{sup} & = \sum_{k=0}^{11} \pi_{t-k,t-k-1}^{sup} \\ \pi_{t,t-12}^{dem} & = \sum_{k=0}^{11} \pi_{t-k,t-k-1}^{dem} \end{cases}$$

2.1.2. Robustness check : alternative classifications

Shapiro introduced several alternative classification methods which we replicated to assess whether the methodology was robust enough. In our version, as the lag order for each VAR is automatically selected (and if we believe the selected lag is correct) there should not be specification error.

Although Shapiro argues that his results are robust to lag selection, as we chose to let said selection be industry-specific, we decided to check how restrictive setting a 12 lag VAR for each sector is in order to find out whether our addition was useful. To do so, we estimate VARs with a maximum number of lags set to 12 and then to 24 and select the order based on Aikake information criterion (AIC) and Bayesian information criterion (BIC). We are then able to compare how this choice of lag based on AIC or BIC differs from 12. When setting the maximum number of lags at 12, we find that, based on the AIC, 12 would be the optimal number of lags in the majority (65%) of cases among all our series. As for BIC, it is more evenly distributed between n=1,2 and 12 lags, the majority being 2 lags (35%) among all our series. When setting the maximum number of lags at 24, we respectively find a majority of n=24,23 lags for AIC and n=1,2 and 12 for BIC without any series of selected order above 15 (see 5.2). What we aim to show, now knowing that, depending on the criterion, more than 50% of the industry specific VARs could be estimated with a number of lag not equal to 12, is that our setting free of this constraint seems reasonable.

We then implement the two alternative methods that are the smoothed-errors classification (to offset possible measurement errors) and the parametric approach. In the latter, each month a sector is no longer binary, i.e either experiencing a supply or a demand shock, but there rather is a probability p_t^K that it is experiencing a shock of type $K \in \{\text{supply,demand}\}$.

The smoothed-errors classification amounts to considering $\sum_{k=0}^{j} \nu_{i,k}^{q}$ and $\sum_{k=0}^{j} \nu_{i,k}^{p}$ instead of simply $\nu_{i,t}^{q}$ and $\nu_{i,t}^{p}$ in the aforementioned classification. The parameter j is an hyperparameter, set to be the same for each sector. In his paper Shapiro tries different values (ranging from 1 to 3) meaning for each month t it is the sign of the (average) j previous months residuals that matter.

In the parametric approach the rationale is that when both errors $\nu_{i,t}^{p}$ and $\nu_{i,t}^{q}$ increase in absolute value, the probability that sector (i) is really experiencing the type of shock determined by the signs increases. We get more confident in the determination of the type of shock experienced as errors depart from zero. Let $\lambda_{i,t} = \nu_{i,k}^{p}.\nu_{i,k}^{q}$ and $z(\lambda_{i,t})$ the number of standard deviations $\lambda_{i,t}$ is from zero. Letting $\phi_{i,t}^{dem} = P[z(\lambda_{i,t})]$, with P the cumulative distribution of a standard Normal law, $\phi_{i,t}^{dem}$ satisfies the requirements we are looking for. Namely, conditional on residuals being of the same sign, as they both increase the probability that sector (i) is experiencing a demand shock increases which makes sense. Conversely, if they were of opposite signs and different from zero, $\phi_{i,t}^{dem}$ would converge toward zero. It follows that $\phi_{i,t}^{sup} = 1 - \phi_{i,t}^{dem}$ can be defined.

2.2. Classification from *Sheremirov (2022)*

The algorithm proposed by Sheremirov(4) is as follows, for each sector i and month t :

1. Compute year-over-year inflation and (real) consumption/demand growth : $\pi_{i,t}$, $c_{i,t}$
2. Classify the sector i as experiencing a demand shock at month t if both inflation and

consumption growth are over their 2001-2019 respective average $\tilde{\pi}_i, \tilde{c}_i$:

$$\mathbb{1}_{i,dem}(t) = \begin{cases} 1 & \text{if } (\pi_{i,t} - \tilde{\pi}_i).(c_{i,t} - \tilde{c}_i) > 0 \\ 0 & \text{otherwise} \end{cases}$$

$$\mathbb{1}_{i,sup}(t) = 1 - \mathbb{1}_{i,dem}(t)$$

3. Classify the shock at month t as:

$$\text{Persistent demand } \mathbb{1}^{pers}_{i,dem}(t) = \begin{cases} 1 & \text{if } \sum_{k=0}^{11} \mathbb{1}_{i,dem}(t-k) \geq 11 \\ 0 & \text{otherwise} \end{cases}$$

$$\text{Persistent supply } \mathbb{1}^{pers}_{i,sup}(t) = \begin{cases} 1 & \text{if } \sum_{k=0}^{11} \mathbb{1}_{i,sup}(t-k) \geq 11 \\ 0 & \text{otherwise} \end{cases}$$

4. If neither condition is verified, month t is classified as transitory demand (if $\mathbb{1}_{i,dem}(t) = 1$) or transitory supply.

The Sheremirov methodology was implemented to assess to what extent classifications derived from Shapiro's methods would be consistent with alternative methods, especially one not based on a VAR estimation. However the distinction it provides between transitory and persistent components makes it really interesting for policy-makers even though the classification is solely backward-looking.

2.3. Proposed classification rule

On this basis we suggest tweaking the classification outlined by Sheremirov, challenging the set number of months (11) for the persistent classification and the pure backward-looking perspective.

The latter can be a problem as the classification does not rule out persistent demand (or supply) vanishing. Consider a sector i and assume month $t-1$ is not labeled as persistent demand because months $t-10$ and $t-12$ are not labeled as demand-driven and let month t be demand-driven. According to Sheremirov's rule, month t is labeled as persistent demand as we have 11 months classified as demand-driven (only month $t-10$ is not). However, if month $t+1$ is not demand-driven, persistent demand vanishes after only one month because at least 2 months are not demand-driven conflicting the criterion. Which in our opinion is kind of an awkward situation as the whole purpose of the persistent component is to be persistent and not to instantaneously disappear. Our methodology solves this, as month t would have never been labeled as persistent demand in the first place due to the forward-looking setting we incorporate to the rule.

On another note, as the first step of the classification below relies on the simple dummy demand-supply classification, we can use both results from the labeling of Shapiro or (step.2 of) Sheremirov. Our aim is to leverage the initial supply-demand classification, decomposing each as transitory-persistent (as Sheremirov did) with both backward and forward-looking perspectives. We add sort of a feedback rule -an ambiguous category- such that the dates for which the forward-looking perspective is not possible (due to unobserved data) are not miss-classified. A month that had been categorized as ambiguous can thus be re-classified once "enough" data have been added.

We propose the following algorithm:

1. Classify month t for sector i as experiencing a demand or supply shock: either through Shapiro's rule (1,2) or step.2 of Sheremirov's algorithm (2.2).

2. We introduce the following modified rule, where K can be debated but we set the baseline as $K = 3$:

$$\text{Persistent demand } \mathbb{1}^{pers}_{i,dem}(t) = \begin{cases} 1 \quad \text{if} \quad \mathbb{1}_{i,dem}(t) + \sum_{k=1}^{K}\{\mathbb{1}_{i,dem}(t-k) + \mathbb{1}_{i,dem}(t+k)\} \geq 2K \\ 0 \quad \text{otherwise} \end{cases}$$

$$\text{Persistent supply } \mathbb{1}^{pers}_{i,sup}(t) = \begin{cases} 1 \quad \text{if} \quad \mathbb{1}_{i,sup}(t) + \sum_{k=1}^{K}\{\mathbb{1}_{i,sup}(t-k) + \mathbb{1}_{i,sup}(t+k)\} \geq 2K \\ 0 \quad \text{otherwise} \end{cases}$$

$$\textit{Ambiguous} \text{ demand } \mathbb{1}^{abg}_{i,dem}(t) = \begin{cases} 1 \quad \text{if } t \in [T-K+1, T] \text{ and :} \\ \mathbb{1}_{i,dem}(t) + \sum_{k=1}^{K}\mathbb{1}_{i,dem}(t-k) + \mathbb{1}_{t\neq T}\sum_{k=1}^{T-t}\mathbb{1}_{i,dem}(t+k) \geq K + (T-t) \\ \textit{i.e almost satisfies pers. but some date ' t + k ' is unobserved!} \\ 0 \quad \text{otherwise} \end{cases}$$

$$\textit{Ambiguous supply } \mathbb{1}_{i,dem}^{abg}(t) = \begin{cases} 1 \quad \text{if } t \in [T-K+1, T] \text{ and :} \\ \mathbb{1}_{i,sup}(t) + \sum_{k=1}^{K} \mathbb{1}_{i,sup}(t-k) + \mathbb{1}_{t \neq T} \sum_{k=1}^{T-t} \mathbb{1}_{i,sup}(t+k) \geq K + (T-t) \\ \textit{i.e almost satisfies pers. but some date ' t + k ' is unobserved!} \\ 0 \quad \text{otherwise} \end{cases}$$

3. If no condition is verified, month t is simply classified as transitory demand (if $\mathbb{1}_{i,dem}(t) = 1$) or transitory supply.

The persistent demand(supply) labeling simply asserts that for a given month t, in the window of the three previous and next months, at least $2K$ have been classified as experiencing a demand(supply) shock. For instance when $K = 3$ this checks that for September 2019, between June and December 2019 (7-month window), at least 6 have been labeled as demand-driven (for persistent demand and vice versa).

The *ambiguous* (ambiguous in the sense of undetermined between transitory and persistent) labeling is pretty similar to the persistent but is only applied to the last K observations. It aims at labeling the months for which we cannot apply the full rule because the forward-looking part simply sums over unobserved data. For instance, when $K = 3$, only the last three observations ($t \in [T-2, T] = [T-K+1, T]$) can be categorized as ambiguous. When assessing the label for $t = T-2$ the condition for ambiguous demand checks if in the range of: the previous 3 months + current month + next $T-(T-2) = 2$ available months, at least $3 + (T-(T-2)) = 5$ have been labeled as experiencing a demand shock.

The labeling is retroactive as once data for the date $t = T+1$ is observed the classification of month $T-2$ -had it been classified as ambiguous- is potentially changed if it either satisfies the "complete" persistent supply or demand criterion. Otherwise it is labeled as transitory.

NB1: with the sample denoted $[1, T]$ *we start the classification at date* $t = 1 + K$

NB2: the classification suggested above does not work for the parametric approach, as the latter simply does not have dummy variables for supply-demand classification but rather probabilities, which impedes the counting rule put in place.

3. Results

Though we managed to compute inflation breakdowns for France, Germany, Spain and the EU27 aggregate we chose to simply look at the results for France. Reason is that it is the country with the least unclassified inflation which increases the confidence we have regarding the different classifications. Still, results presented below appear to be true for the remaining countries as well.

Figure 1 and 2 show the correlation between the different methods of classification for both the supply and demand components. The main message is that, despite the concerns we had regarding methodological details and what appeared as crucial differences, all methods appear to produce consistent components, with correlations ranging from 0.7 to 0.99.

Moreover as we previously mentioned compared to the original paper of Shapiro, that uses a fixed VAR(12) for each sector, we opted for the lag selection via BIC or AIC. Though selected orders are usually different (Figure A3 and A4) and thus leading to different fitted models, the final overall classification is usually close with correlation of 0.9 for demand and 0.92 for supply. This alleviates some potential concerns that we had regarding sector-specific model selection.

Another interesting feat is that the components derived from the Sheremirov's algorithm, despite not being model-based, still strongly correlate with the output of Shapiro's different methodologies. This increases the overall confidence we have in the results and we decide to look more closely at the output of our proposed methodology (which is, as a reminder, the same as baseline Shapiro for the simple demand/supply classification but also has the persistent/transitory features).

FIGURE 1. *Cross-correlations : demand component for France*

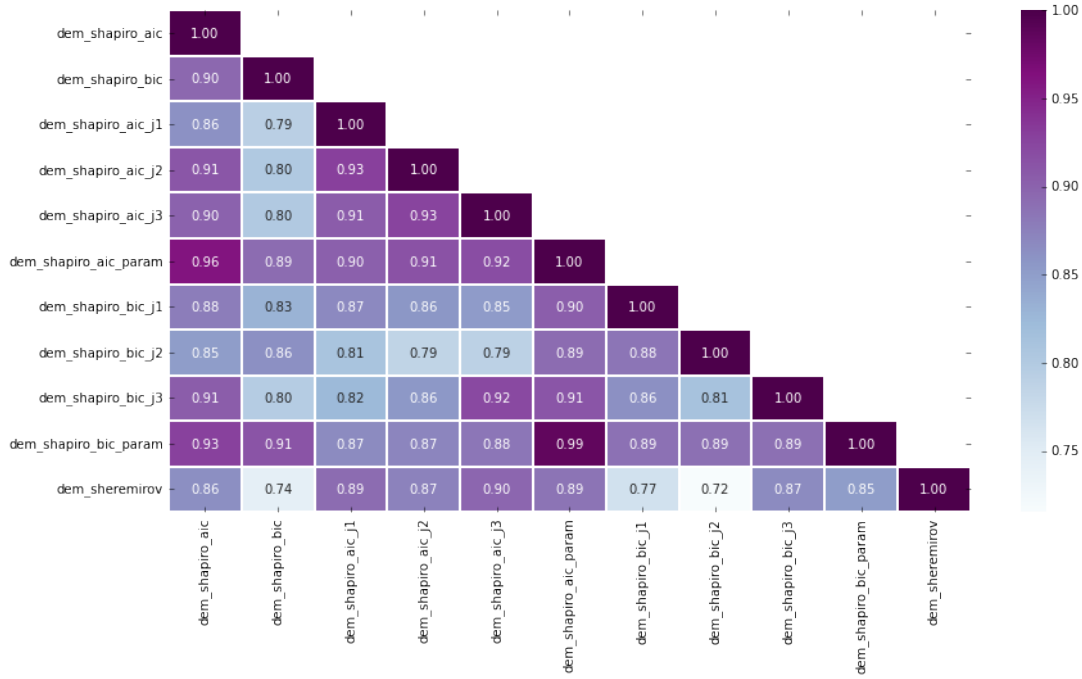
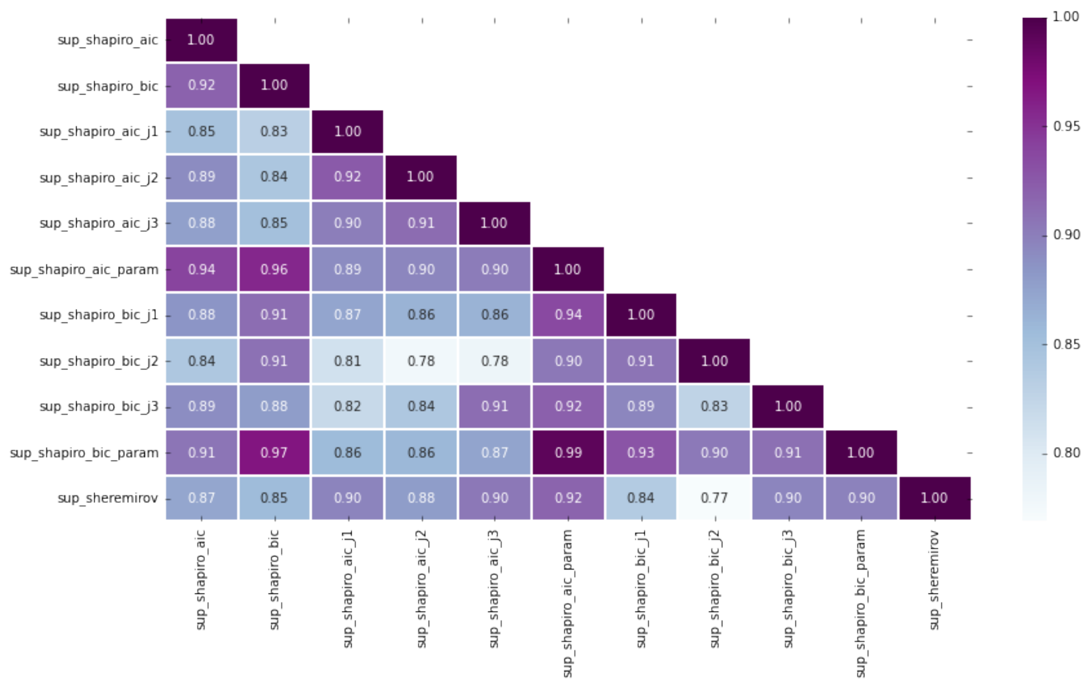
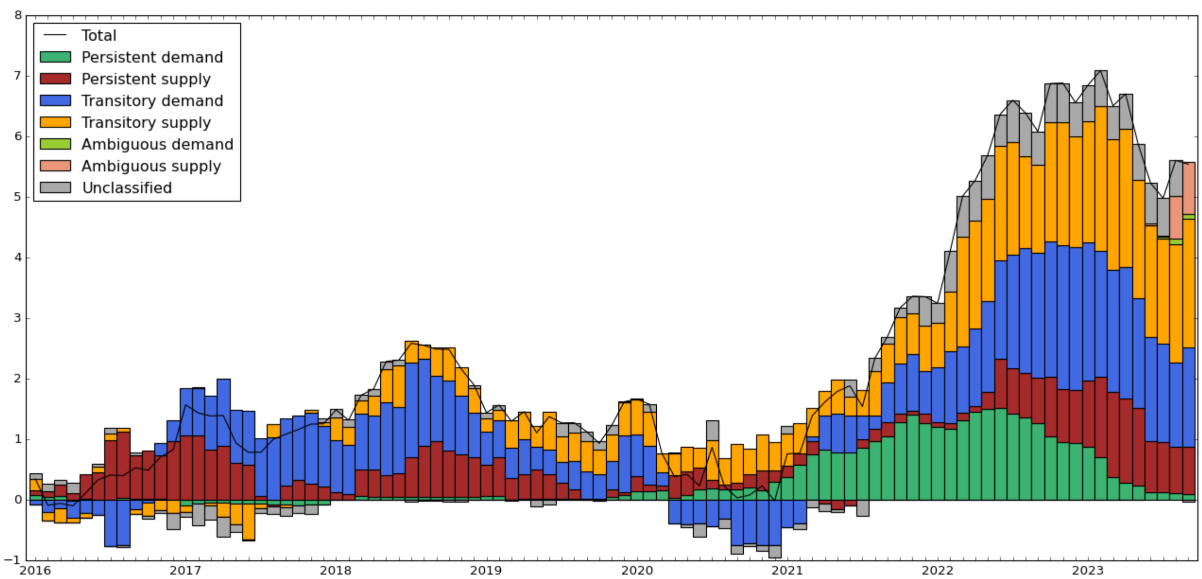


FIGURE 2. *Cross-correlations : supply component for France*



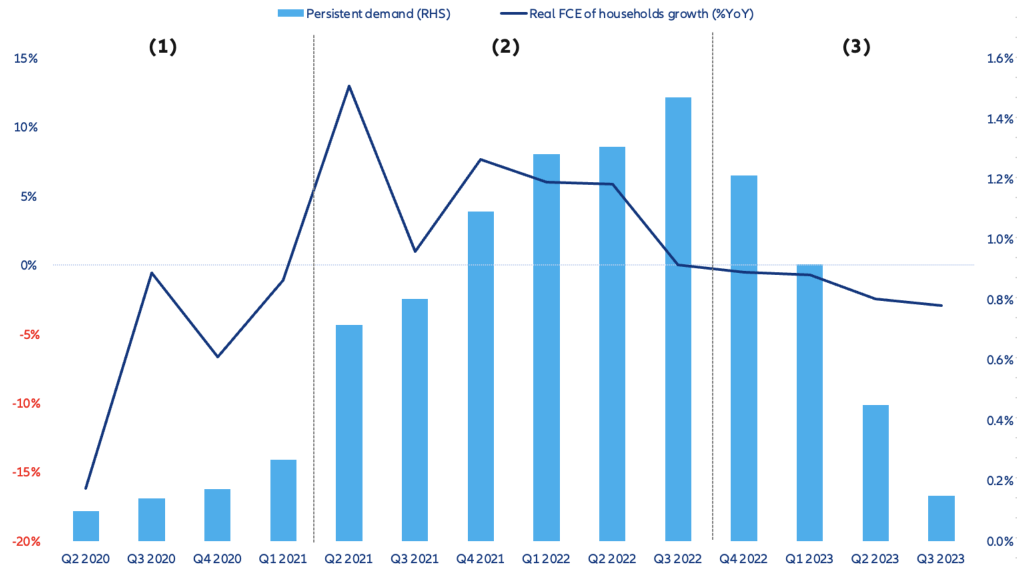
Our proposed inflation (year-over-year inflation growth rate) classification for France is displayed just below Figure 3 (see Figure A5 for the pure replication of Shapiro's work). This streamlit app allows you to check the results for different countries and classification rules which we can't all include in this report. We see clearly that the transitory demand takes a dive after the first French lockdown (March 2020) before booming again when COVID regulations softened. We then see the supply component arising (persistent+transitory) soon after, which is consistent with the supply chain disruptions induced by lockdowns and restrictions. Supply also accounts for most of inflation from early/mid 2022 onwards, in line with the economic shock that followed the invasion of Ukraine and the disruption to the important economic input that is energy.

FIGURE 3. *Proposed HICP (YoY%) classification for France*



In order to externally assess its relevance, we compare the contribution of the demand component in the YoY% HICP to the final consumption expenditure (*FCE*) of households in France using Eurostat data. We use quarterly Eurostat data and thus convert our monthly classification into a quarterly. We plotted the real growth rate of FCE of households next to our HICP decomposition to see whether a sustained positive real FCE growth corresponds to an increase in persistent demand. Figure 4 displays the results.

FIGURE 4. *Real FCE growth (LHS) and persistent demand (RHS) in our HICP breakdown*



First, we argue that the positive persistent demand contributions in 2020, and the negative persistent demand in early 2021, on Figure 3 are most likely due to noise in the data. Both mentioned contributions are negligible in absolute value (<0.2%) but mainly negligible relative to other contributions. As an improvement to our methodology, it would be better to implement an *unclear* class (which is different from the *ambiguous* component) *when both residuals are too close to zero*[1] which make information inferred from signs not so much reliable. Thus, the contributions of 2020, period *(1)* on Figure 4, are considered as negligible in the discussion below.

When assessing the demand contribution, especially around the Covid period, it is important to remember how the classification is done. In 2020, spending opportunities were severely curtailed twice and household consumption nosedived. However, we know that the first reduction (negative demand shocks) in consumption during the initial lockdown, was dampened by a strong rebound between June and October 2020 (household expenditures on goods rebounded above pre-pandemic levels). This can be seen on the chart with a little spike in inflation. The algorithm mainly classifies inflation as transitory around that time as it has knowledge of the future rebound in demand: in the words of our methodology, for each month of this period there are not enough months around that are all similarly classified, precisely because of this rebound.

[1]We could think of something similar to what was implemented in the parametric approach by taking the product of residuals, computing the number of standard deviations from zero and setting a threshold under which the product is deemed too little, meaning information inferred would be too unreliable

From early 2021 onwards, what is striking is that household real final consumption continuously increased (period *(2)* Figure 4). This also explains why the last few months of 2020, during the second lockdown, were only classified as transitory as the algorithm had knowledge of the positive demand shocks occurring at the beginning of 2021. Thus, from Q2 2021 onwards we can see on Figure 4 that the persistent demand component is no longer negligible relative to other classes and the rise of persistent demand in inflation, for 6 quarters straight, appears to extensively correlate with an extended period of positive real growth rate of household consumption expenditures. Conversely, as this real growth rate turned negative (period *(3)*) after late 2022 and especially in Q2 and Q3 2023 we notice the strong decrease of persistent demand contribution to inflation, basically amounting to zero as of late 2023. After 4 successive quarters of negative real household final consumption expenditure growth, persistent demand pressures on inflation disappeared.

4. Bibliography

References

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[4] Viacheslav Sheremirov. "Are the Demand and Supply Channels of Inflation Persistent? Evidence from a Novel Decomposition of PCE Inflation". Current Policy Perspectives, Federal Reserve Bank of Boston, 94983, 2022.

Appendix 5.

5.1. ADF test results (differenced log demeaned prices and quantities, EU27) at 1%, 5% and 10% levels

	1% (price)	5% (price)	10% (price)	1% (quantity)	5% (quantity)	10% (quantity)
% of null rejection (ADF)	46.9%	63.2%	65.3%	93.9%	95.9%	95.9%
% of null rejection (ADF - linear trend)	43.9%	61.2%	65.3%	93.9%	95.9%	98%
% of null rejection (ADF - quadratic trend)	40.8%	60.5%	63.9%	92.5%	95.2%	97.3%

5.2. Selection of lags with AIC and BIC

FIGURE A1. *Histogram of selected lag orders among all series following the AIC (max lag = 12)*

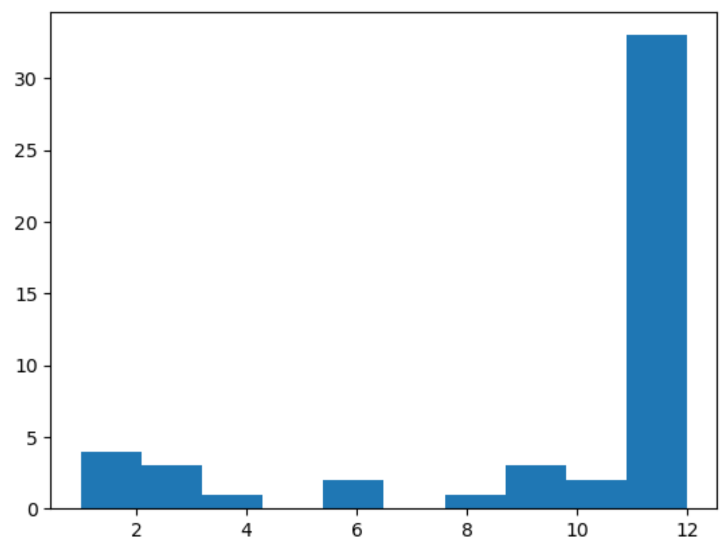

FIGURE A2. *Histogram of selected lag orders among all series following the BIC (max lag = 12)*

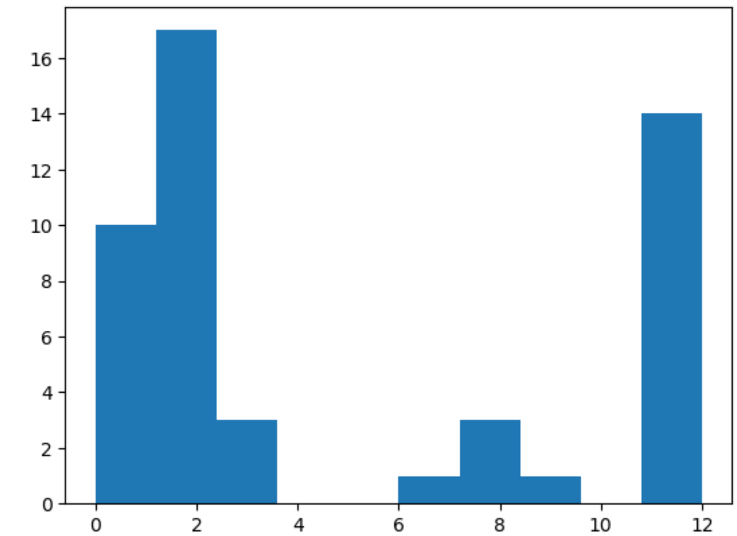

FIGURE A3. *Histogram of selected lag orders among all series following the AIC (max lag = 24)*

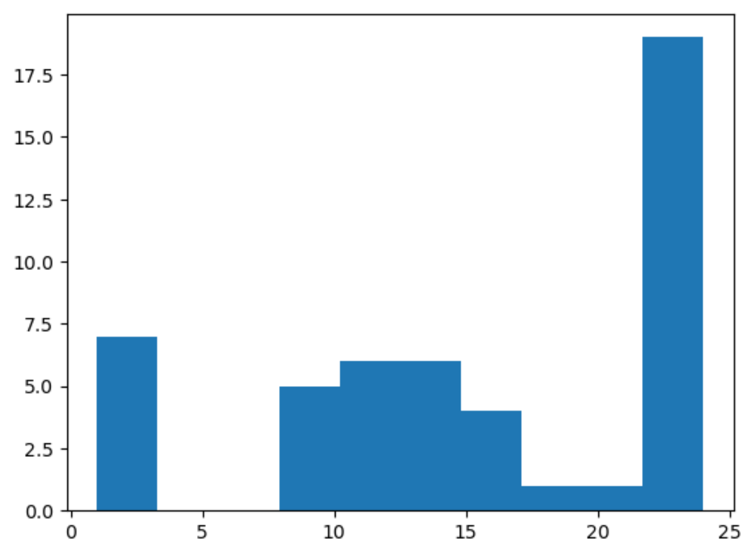

FIGURE A4. *Histogram of selected lag orders among all series following the BIC (max lag = 24)*

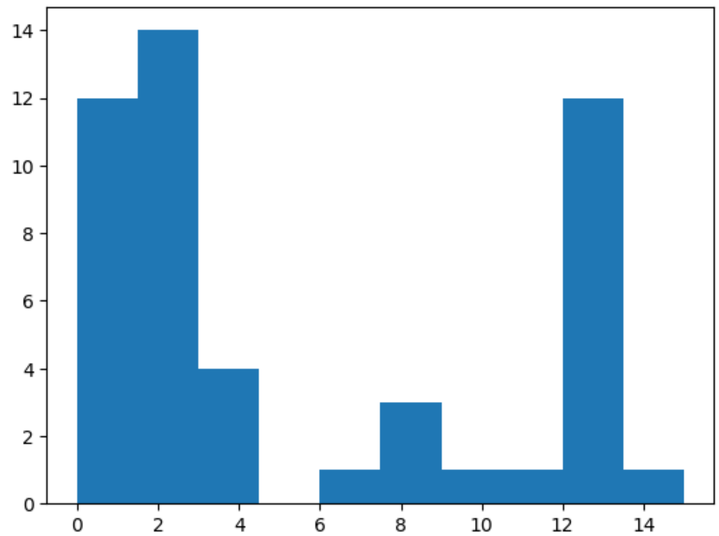

FIGURE A5. *Shapiro's HICP (YoY%) classification for France*

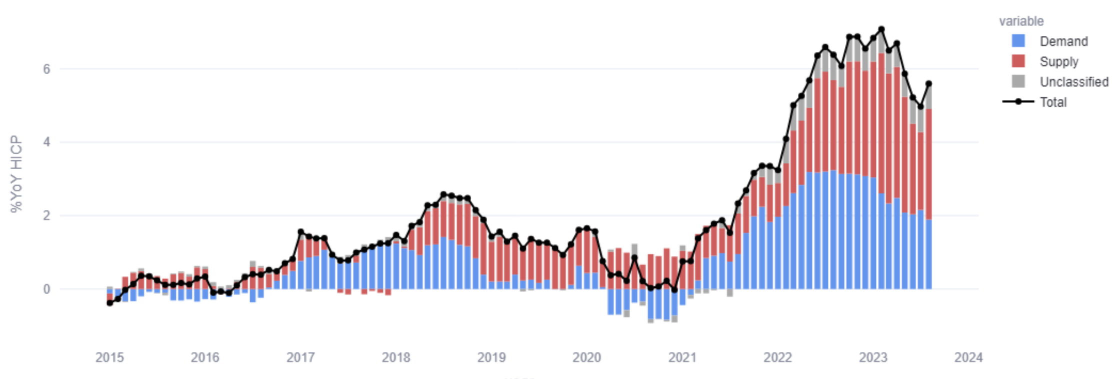

FIGURE A6. *French household final consumption expenditure real growth rate*