Banco de Portugal
Banco de Portugal Economic Studies, Vol. IX, No. 2

The inflation process in Portugal: the role of price spillovers

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April 2023

Abstract
The recent rise in inflation was initially driven by external shocks and restricted to some items, becoming increasingly entrenched over 2022. In this article, the role of price spillovers in the generalization of inflationary pressures is analysed. Spillover effects rose in the post-pandemic period and are more important for a longer period due to a higher transmission across sectors. This suggests that relative price changes are more likely to propagate to underlying inflation as they echo more into other components. The measure of *common inflation* built confirms this trend as it shows that co-movement across a large number of prices has been the main driver of headline inflation. **Keywords**: inflation, spillover effects, Bayesian VAR (JEL: C11, C38, E31)

1. Introduction

Inflation in Portugal has surged significantly since July 2021, attaining levels not seen in the preceding thirty years (8.1% on average in 2022). After nearly a decade of inflation consistently below 2%, the shift in the inflationary process happened remarkably fast, similarly to what occurred in most advanced economies. The recent upward trend is the outcome of different, but interconnected and mutually reinforcing factors. The economy's reopening following the pandemic, aided by economic policies supporting activity, prompted a quick and intense recovery characterized by high demand for goods that the supply chains were unable to adequately fulfill. Additionally, the invasion of Ukraine by Russia led to an increase in import prices for energy and food items, exacerbating supply-side bottlenecks. The higher costs of these commodities were translated directly into higher consumer prices. In addition, they may have propagated through the production chain due to spillovers of inflationary pressures across sectors,

Acknowledgements: The authors thank Pedro Duarte Neves, Nuno Alves, João Amador, António Antunes, the other participants in an internal seminar of the Economics and Research Department of Banco de Portugal and an anonymous referee for their comments. A special thank you to M. Lombardi and E. Zakrajšek for giving access to a preliminary version of their working paper. The analyses, opinions, and findings expressed in this article are those of the authors and do not necessarily coincide with those of Banco de Portugal or the Eurosystem. Any errors and omissions are the sole responsibility of the authors.

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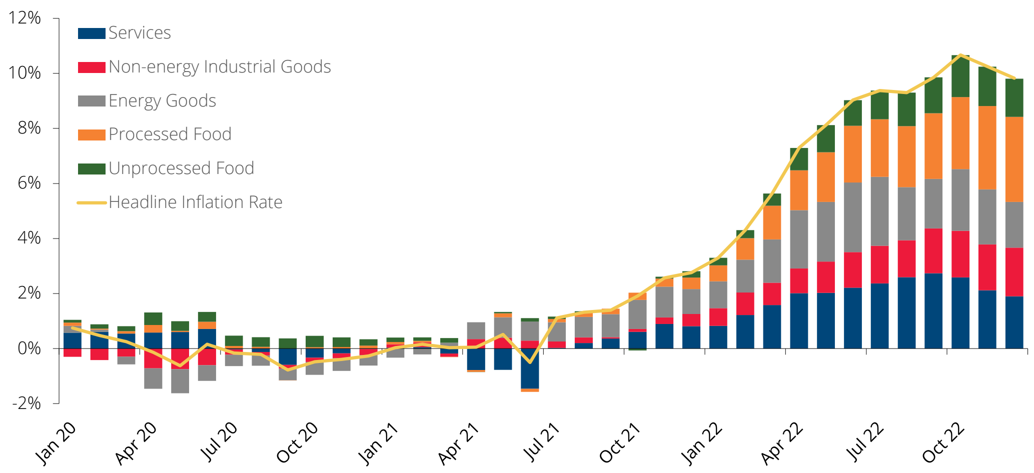

FIGURE 1: Year-on-year HICP inflation rate and its decomposition | Percentage

Sources: Eurostat and authors' calculations.

turning into a broad-based inflation.

Initially, the hike in prices was restricted to a limited number of items. In December 2021, the share of items of the Harmonized Index of Consumer Prices (HICP) with a year-on-year rate of change higher than 6% was around 10%.[1] The relative price changes resulting from supply and demand imbalances took place on items with comparatively flexible prices, such as oil, which boosted fuel prices. These seemed, at the beginning, short-lived and reversible movements in the inflation rate. However, with the invasion of Ukraine, food items were abruptly impacted and, to a smaller extent, services and non-energy industrial goods as well, as reported in Figure 1. The share of items in the consumption basket with prices growing at a pace faster than 6% grew to 49% in December 2022. The generalization of inflationary pressures suggests that the greater dynamism of the prices of more volatile goods, affected by the large shocks, was extended to the typically more stable components, which is currently visible in an increase of the underlying inflation measures.

There is evidence in the literature that a high inflation environment is characterized by higher price spillovers across sectors because it amplifies the transmission of both economy-wide and idiosyncratic shocks to all prices (BIS (2022)). One consequence of this is that relative price changes are more likely to propagate to underlying inflation as they echo more into other components. Therefore, it is important to better understand how price spillovers are currently shaping the growth of prices in Portugal and how they are associated with broad-based inflation. In this article, these topics are explored on the basis of HICP data by employing two complementary and empirical approaches.

To begin, the spillover effects of inflationary pressures across the main HICP components are measured and their relevance to the variation of prices over time is assessed. This entails the estimation of a Bayesian Vector Autoregression (BVAR) model,

1. The data considered includes 126 items with a 4-digit level of disaggregation, under the Classification of Individual Consumption by Purpose (COICOP).

drawing on the work developed by Borio *et al.* (2023). The estimates from the model are used to compute generalized impulse response functions (GIRF) and the respective matrices of generalized forecast error variance decomposition (GFEVD) for different horizons. The off-diagonal elements of such matrices express the fraction of the variance in each component's inflation rate that results from changes in other components, controlling for the macroeconomic factors driving prices. A conclusion of this analysis is that price spillovers rose in the post pandemic period, meaning that idiosyncratic shocks in each component are transmitted more intensely across sectors. The most significant change in the sources of effects when comparing the period from 2011 until 2019 with the one that includes data until 2022 stems from processed food items. The rise in spillovers between the two sub-samples is not due to a higher contemporaneous correlation of idiosyncratic shocks but rather to the transmission of those through the lag structure of the model, with the effects remaining relevant for longer periods. Finally, when the analysis is extended by including producer price indices (PPI) in the model to examine the dynamics of spillover effects along the production value chain, the results for HICP still hold but the index of total spillovers more than doubles.

Next, this article aims to validate the result of a recent increase in spillovers with a totally diverse approach. A measure of *common inflation* is constructed to assess whether hikes in prices have been driven by common or idiosyncratic shocks and confirm the generalization of the inflationary pressures in the post-pandemic period. This measure is a statistical instrument that captures co-movement across a panel of disaggregated HICP items using a dynamic factor model (DFM) in line with the one developed by Luciani (2020). The inflation rate of each item is decomposed into two components: a common component, which corresponds to price changes that are attributable to economy-wide factors, and an idiosyncratic part that captures fluctuations over time specific to that item or a small group of them and measurement errors. According to Smets *et al.* (2018), the impact of spillovers should be reflected in this common component, which is found to increase substantially over 2022. Additionally, the instabilities and unusual co-movement across many prices resulting from the Ukraine invasion by Russia are accounted for as their impact on parameter estimation in February 2022 is analyzed. The model suggests that headline and *common inflation* have generally been synchronized over the past 20 years. In the end of 2022, the two surged above 8%, as the common component explains a larger share of the total variability of individual price changes.

One could expect that once the external shocks began to subside, inflation would decay. However, since the most affected items have moved jointly with many others, the impact caused by those has been converted into broad-based inflationary pressures. Their magnitude, aligned with the higher connectedness of prices, have contributed to recent broad-based inflation wave.

Related literature. This article draws on two main streams of the empirical literature on inflation. The first part of the article follows closely on the work by Borio *et al.* (2023) and its application in BIS (2022), in which they measure the spillovers of prices across sectors and how they have changed over time. This study resorts to a BVAR model to study the relationships across different categories of the U.S. Personal

Consumption Expenditures (PCE) deflator, controlling for macroeconomic variables like economic slack or commodity prices, that account for the common drivers of several PCE components. Borio *et al.* (2023) find evidence of stronger spillovers in the high inflation regime that preceded the Great Moderation. Gasoline and food items stand out as the main origins of spillovers. This analysis is extended in BIS (2022) by adding producer prices to the model, which leads to the conclusion that spillovers are higher across PPI components and that they are stronger in the direction from PPIs to PCEs rather than otherwise. The methodology used in this article and in Borio *et al.* (2023) comes from the seminal work for the literature on financial volatility and international business cycle spillovers by Diebold and Yilmaz (2009). This was extended in Diebold and Yilmaz (2012) by setting aside the need for a Cholesky-type structural identification scheme, which makes results dependent on the order of variables in the VAR.

Borio *et al.* (2023) present a two-regime view of inflation. While inflation tends to be selfstabilising in the low-inflation regime, it is especially sensitive to relative price increases in the high-inflation one. Fiore *et al.* (2022) argue that an increase in sectoral price spillovers can signal a transition from a low to a high inflation regime. Corsello and Tagliabracci (2023) focus on the transmission of energy price shocks to other inflation components, on the basis of a Structural VAR for the euro area and Italian data. They find a sizable pass-through to food inflation, but a more limited transmission to core inflation. Even though this methodology is used in the current study to estimate inflation connectedness within the Portuguese economy, this method has also been used to analyse spillovers between countries (Álvarez *et al.* (2019) and Hałka and Szafranek (2016), for example). The results in these studies suggest that spillovers to core components are weaker than to more volatile ones.

Price spillovers are found to increase when the sample is extended to include data up to 2022. The fact that spillovers increase in a period of high inflation is in line with the literature on non-linear transmission of shocks to inflation and non-linearities in the output-inflation nexus (see Dupasquier and Ricketts (1998) for a review). Bäurle *et al.* (2021) analyse the transmission of external shocks to Swiss inflation, concluding that a part of the impact is likely mechanical (direct), but general equilibrium effects (spillovers) are important as well. The importance of spillovers effects also seems to vary with the underlying shocks, with energy playing a prominent role. Bobeica *et al.* (2019) find shock-dependent pass-through effects of labor costs to prices, which are systematically lower in periods of low inflation as compared to periods of high inflation. Forbes *et al.* (2021) find that the Phillips curve is linear and steep in periods of high inflation, which is consistent with evidence of downward nominal wage and price rigidity, but flat otherwise. Ball and Mankiw (1994) show that in a staggered price setting environment with the presence of menu costs large shifts in relative prices correspond to adverse supply shocks and that this effect is asymmetric, given that when shock raises some firms' desired prices and lowers others', the desired increases trigger greater price adjustment than the desired decreases.

If the post-pandemic period involves a stronger transmission of relative price changes across HICP components, an idiosyncratic shock to a component can become more easily a broad-based movement in the headline inflation rate. BIS (2022) argue that a period of low inflation is characterized by lower inflation volatility, and this decrease happens because the covariance between individual prices changes. Thus, spillovers are expected to increase their role as drivers of overall HICP in the recent inflationary period. To assess this, each item of the consumption basket is decomposed into an idiosyncratic component and a common component. This common component tries to capture a broad-based and sustained increase in prices and is estimated on the basis of a DFM, drawing closely on Luciani (2020). Smets *et al.* (2018) conclude, on the basis of the results of a multi–sector dynamic stochastic general equilibrium model, that the impact of spillovers tends to be included in the common component of a DFM. Moreover, they conclude, resorting to US PPI and PCE data for 1970-2007, that, due to price stickiness along the supply chain, pipeline pressures are an important source of inflation persistence and volatility.

Several articles analyse inflation developments by separating broad-based movements from idiosyncratic ones (Boivin *et al.* (2009), Kaufmann and Lein (2013), De Graeve and Walentin (2015), Dixon *et al.* (2014), Cristadoro *et al.* (2005), Amstad *et al.* (2017), etc.). Some of them resemble the current article more because they restrict the dataset of analysis to consumer prices at a detailed level (Borio *et al.* (2021), Maćkowiak *et al.* (2009), Conflitti (2020)). The measure that most resembles the approach adopted in this article is the one of Reis and Watson (2010), which try to quantify "pure" inflation from a dataset of disaggregated U.S. inflation items. This measure differs from the *common inflation* indicator computed in this article due to additional technical constraints imposed on the estimation. In addition, in this article the overall *common inflation* measure is constructed by aggregating the common component of each detailed consumer price item with the original HICP weights, thus preserving the original structure. In the same vein, Bańbura and Bobeica (2020) use a generalized dynamic factor model based on data across 12 euro area countries to construct the Persistent and Common Component of Inflation index. This measure excludes from the common component cycles with a length shorter than three years. Some of these studies analyse the properties of the underlying inflation indicators obtained, namely their forecasting ability of the headline. This analysis is beyond the scope of this article.

An extension of Luciani (2020) assesses the impact of the Covid-19 pandemic on prices. This is achieved with a counterfactual built by estimating the model up to the beginning of the pandemic and comparing the common component obtained with the result from the full sample estimation. Potjagailo *et al.* (2022) apply this methodology to U.K. inflation and extend it by considering the impact of the Ukraine invasion by Russia from February 2022 onward, finding similar results to the ones presented here.

Roadmap. The rest of the article is organized as follows. Section 2 presents the measures of spillovers across HICP components for the time frames considered. Section 3 focus on the construction of the *common inflation* indicator and the role of price spillovers on the recent generalization of inflationary pressures. Section 4 concludes with final remarks.

2. Price Spillovers

This section measures price spillovers across the five main components of the HICP. For that purpose, a BVAR model is estimated in line with the one in Borio *et al.* (2023), to analyse how year-on-year rates of change of the price index of the components are affected by a specific shock in each of the other ones over time, when accounting for the developments in the main macroeconomic drivers of inflation as exogenous variables.

2.1. Model Specification

The infinite moving average representation of the BVAR model allows to compute generalized impulse response functions (GIRF) for different horizons and then to construct static spillover measures, as shown in the work by Diebold and Yilmaz (2009, 2012). While the traditional impulse response function answers the question of an impact hitting the system if no other shocks happen, the GIRF considers the situation of a multivariate model with contemporaneous correlated shocks by adjusting for them on the basis of the estimated parameters of the variance-covariance matrix (Koop *et al.* (1996)). In the application of this article, the restrictions imposed by a recursive ordering of the endogenous variables entering the BVAR would be difficult to justify from a theoretical perspective. The approach followed in this article does not require the orthogonalization of the shocks and thus is invariant to the ordering of the system. Furthermore, it fully accounts for the historical patterns of correlations across errors, which is not true in a Structural VAR. Assuming the property of Gaussianity, the GIRF for a shock to a variable j at horizon h is given by:

$$\gamma_j\left(h\right) = \; E_{t-1}\left(x_{t+h} \middle|\; \varepsilon_{j,t} = 1\right) - E_{t-1}\left(x_{t+h}\right) = {\sigma_{jj}}^{-\frac{1}{2}} A_h \Sigma e_j, \tag{1}$$

where e_j is a selection vector with unit values in the j^{th} position and zeros elsewhere. It is possible to extract each entry from the vector of GIRFs, so that $\gamma_{ij}\left(h\right)$ corresponds to the response of the variable i to a shock to the variable j for the horizon h.

Then, GIRFs can be used to construct the matrix with the general forecast error variance decomposition at h-horizon with each element calculated as:

$$\lambda_{ij}(h) = \frac{\sum_{l=0}^{h} \gamma_{ij}(h)^2}{\sum_{j=1}^{N} \sum_{l=0}^{h} \gamma_{ij}(h)^2}. \tag{2}$$

Given that shocks are not orthogonal, the sum of contributions to the forecast error variance do not necessarily sum to unit and the following normalization, suggested by Diebold and Yilmaz (2012), is imposed:

$$\widetilde{\lambda}_{ij}\left(h\right) = \frac{\lambda_{ij}\left(h\right)}{\sum_{l=1}^{N} \lambda_{il}\left(h\right)}. \tag{3}$$

The main diagonal of the matrix $\widetilde{\lambda}_{ij}(h)$ defines own variance shares, i.e. the fraction of the h-step-ahead forecast error variance of variable i explained by shocks to x_i, while the remaining entries $\widetilde{\lambda}_{ij,i\neq j}(h)$ are cross variance shares, defined as spillover effects. These correspond to the fractions of the h-step ahead error variances in forecasting the variable i due to shocks to a variable j, when $i \neq j$. Each column of the matrix $\widetilde{\lambda}_{ij}(h)$ shows the spillover effects from variable x_j to all variables $x_{i,i\neq j}$, in the role of x_j as an origin of spillovers. Each row of the matrix $\widetilde{\lambda}_{ij}(h)$ defines the spillovers received by variable x_i from shocks to all variables $x_{j,i\neq j}$, in the role of x_i as a destination of spillovers. Finally, an index of total spillovers is constructed in order to capture the sum of spillover effects across variables relative to the total forecast error variation:

$$S_t(h) = 100 \frac{\sum_{i,j=1,i\neq j}^{N} \widetilde{\lambda}_{ij}(h)}{\sum_{i,j=1}^{N} \widetilde{\lambda}_{ij}(h)}. \tag{4}$$

2.2. *Data and Estimation*

The data used is the HICP at the two-digit level of disaggregation of the Classification of Individual Consumption by Purpose (COICOP): unprocessed food (UNP), processed food (PF), energy goods (ENG), non-energy industrial goods (NEIG) and services (SERV).[2] Log changes were considered as they allow to extract the decomposition of the shocks directly from the model, without retrieving the deterministic trend that tends to dominate the results with data in levels.[3] Although more disaggregated versions of the model have been estimated, results over different sub-samples proved more stable at this level of aggregation. This is also the most common level of analysis of HICP developments for euro area countries. As an extension, upstream price spillovers are also investigated by including producer price indices in the model. A level of aggregation of PPI items similar to the one of the HICP is considered for consistency of the analysis.

Seasonally and calendar adjusted HICP monthly data was provided by the European Central Bank (ECB). The BVAR was estimated over two sub-samples: the first starts in January 2011 and ends in December 2019 while the second is extended up to December 2022. The selection of time frames was chosen based on two key considerations. Firstly, it's well-established that spillover effects may vary over time. Given the data availability for the PPI series that starts in 2011, for coherence the results for the two versions of the model were estimated with the same time window. Nevertheless, Figure **??** of the Appendix reports the results obtained with different sample starting dates. The main results still hold for the time frames tested, providing further confidence in the validity of the conclusions here presented. Moreover, to ensure a sufficient number of degrees of freedom, the last years of the sample are not isolated from the period before.

The model includes six lags of the endogenous variables. It comprises also a set of exogenous variables to capture the macroeconomic shocks that potentially affect all

2. Note that the statistical production, in particular price collection, were affected by restrictions imposed during the pandemic. Some prices had to be collected using alternative sources and others were imputed (check Statistics Portugal press release of the April 2020 CPI). It is not possible to infer how this may have affected the results presented, but its impact is expected to be limited, given that the share of expenditure in the HICP affected by imputation quickly became negligible after the initial months of the pandemic.

3. For further detail on the Bayesian VAR estimation in rates of changes, check Ferroni and Canova (2021).

HICP components at the same time. The endogenous part of the BVAR thus models the remaining drivers of prices: idiosyncratic shocks that may be transmitted across HICP components. The exogenous variables considered include the short-term interest rate, oil prices in euros and the import deflator excluding energy goods, the year-on-year growth rate of hourly compensation per employee and the amount of slack in the economy as measured by the unemployment gap.[4] [5] The last two were included with a three-month lag and interpolated to monthly frequency using the Litterman method (Litterman (1983)). Dummies were included to account for Value Added Tax rate changes that took place in January and November 2011 and March 2012 and that did not affect all items uniformly. For the estimation of the BVAR, a Litterman/Minnesota prior was considered, along with with the following parameterization: $\lambda_1 = 0.1$, $\lambda_2 = 0.99$, $\lambda_3 = 1$, $\lambda_4 = \infty$, $\lambda_5 = \infty$, 500 iterations and a burn-in percentage of 10%.

2.3. *Main Results*

Figure 2 shows the estimated 12-month horizon forecast error variance decomposition for the two sub-samples in the form of matrices, where the darkest color denotes higher spillover effects from the source component (in columns) towards the destination component (in rows). Each element reports the share of the variance of the year-on-year rate of change in the price of each aggregate that is explained by a shock in each of the remaining ones, controlling for common and generalized drivers of inflation.

Price spillovers rose in the post-pandemic period, meaning that idiosyncratic shocks in each component are transmitted more intensely through the production chain and have a greater impact on the price volatility of the others. Even though the own variance shares (the main diagonal of the matrix) explain the majority of the total variance of forecasting errors, this shift may be relevant for the inflation dynamics. In the shorter sub-sample, it is worth noting the effects of idiosyncratic changes to unprocessed food prices on processed food items (21%), as the former is an essential input for the production of the latter, and in both energy and non-energy industrial goods aggregates, with magnitudes of about 8% and 9%, respectively. Besides these, one must highlight the inflationary pressures originated from non-energy industrial goods towards processed food prices, summing up to 8,5%.

With the extension of the sample period until the end of 2022, not only the bilateral spillover effects became more intense, but also new channels of transmission emerged. The increased connectedness in periods of higher inflation is also found in the work by Borio *et al.* (2023). In this case, the role of processed food as a source of effects gains relevance. A shock to this component now generates substantial price spillovers for unprocessed food, non-energy industrial and energy goods, in a descending order of magnitude. Changes in the prices of energy goods also show a stricter co-movement

4. Unemployment gap is measured as the difference between observed and trend unemployment rates. For further details on the methodology to compute the trend unemployment rate, see Duarte *et al.* (2020).

5. Data points for 2022 Q4 for the import deflator excluding energy goods and hourly compensation per employee correspond to projections published in Economic Bulletin of Banco de Portugal December 2022.

with the prices of food items as a whole, summing to 18,5% in total. These two results corroborate with the ongoing impact of the invasion of Ukraine on food and energy. Furthermore, the NEIGs stand out as the origin of spillover effects, i.e. through contagion of the remaining categories, mainly influencing processed food prices, possibly because of their return to growth in 2021 after several years of decline.

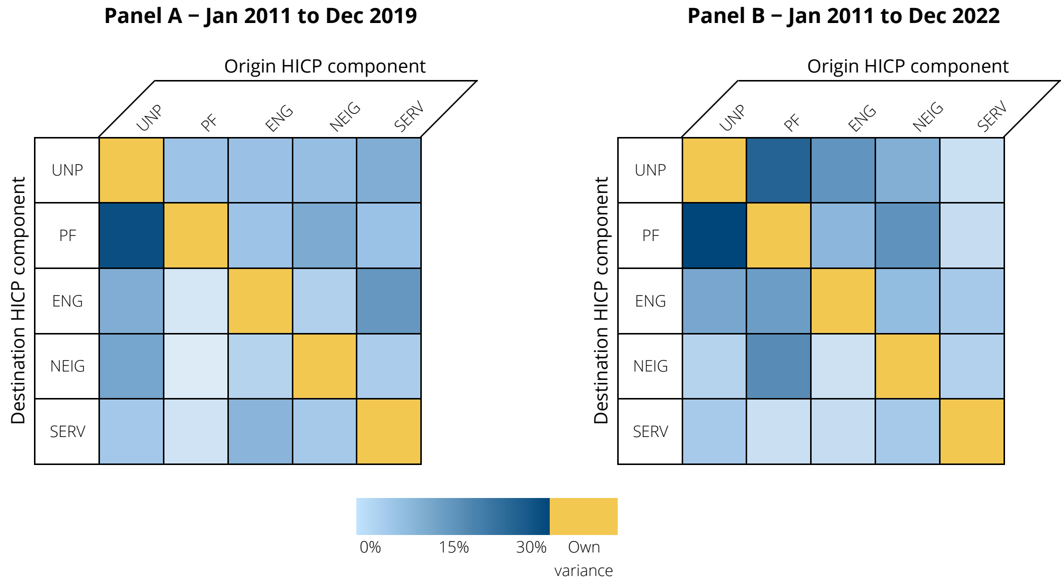

FIGURE 2: Spillover effects across HICP components for a 12-month horizon | Percentage

Sources: ECB, Statistics Portugal and authors' calculations. Notes: UN – Unprocessed Food; PF - Processed Food; EN - Energy Goods; NEIG - Non-energy Industrial Goods; SERV – Services. The spillover effect is assessed by the proportion of the variance of the year-on-year rate of change in the price of each aggregate that is explained by a one standard-deviation shock in each of the remaining HICP components, controlling for common and generalized variations in the economy. The reading of the matrix is as follows: each element represents the percentage of the variance of the year-on-year rate of change of the price of the component in the respective row explained by a one standard deviation shock to the year-on-year rate of change of the price of the component in the respective column. The goal is to analyse the spillover effects across categories, so the diagonal elements, which are based on GIRFs of a category to impulses on itself, are omitted (in yellow). The darkest the blue color the higher is the magnitude of the spillover effects. Given the normalization presented above, the sum of contributions to the forecast error variance of each variable, presented in each line, sums to unit. The same is not necessarily true when summing the contributions from each variable, given by each column. The respective percentage values for each element of the two matrices are shown in Table A.1 of the Online Appendix.

The analysis of the aggregate effect of each component as destination or source of effects confirms the rise in the intensity of spillover effects. For this assessment, the following measures were calculated for a 12-month horizon: sum of the percentage change in the price of each component that is explained by a shock in each price of the remaining components (destinations), and sum of the percentage change of the other categories' price volatility explained by a shock in each component (sources).

Figure 3 compares the directional spillovers across the two sub-samples. Prior to the pandemic, processed food items were the most affected by pressures stemming from the other components, which explain more than 40% of its forecasting variance unrelated to exogenous variables. The categories of unprocessed food and energy goods also were the destination of a considerable level of indirect effects. Conversely, the main source of spillover effects to other goods and services was the unprocessed food aggregate, being responsible for almost 43% of their total variance, mainly due to its impact on the processed food component. The degree of spillovers increases when the sample is extended to 2022. Processed food remains as the most affected, but now unprocessed food is very close with indirect effects accounting for 39,4% of its variation. On the sources side, the most significant change stems from the processed food component, which becomes the main origin of spillovers (42,9%). The relevance of the indirect effects triggered by energy goods (21,8%) and NEIG (30,1%) also goes up.

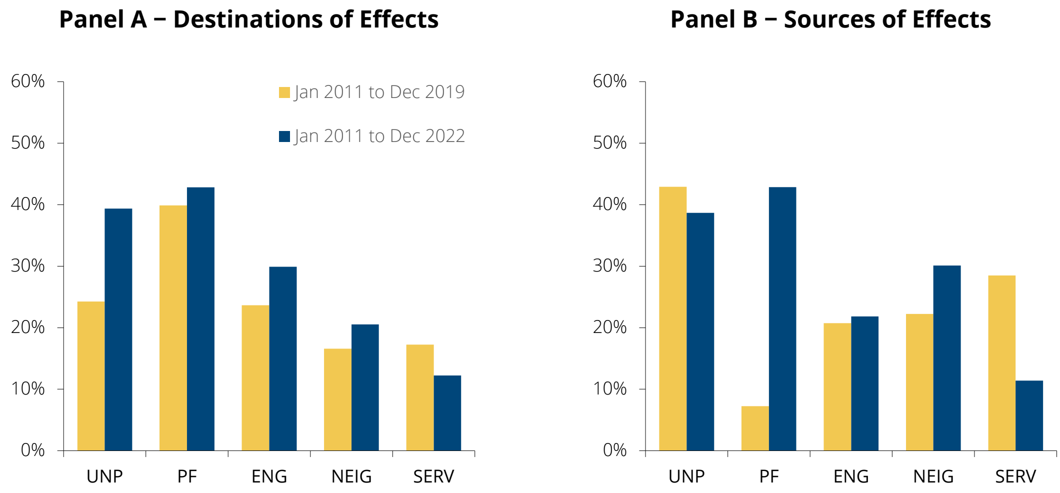

FIGURE 3: Destination and sources of spillover effects by HICP component | Percentage

Sources: ECB, Statistics Portugal and authors' calculations. Notes: Destinations of effects are calculated by summing the non-diagonal elements of each row of the matrix in Figure 2 (Panel A). Sources of effects are calculated by summing the non-diagonal elements of each column of the matrix in Figure 2 (Panel B).

In order to ascertain the reliability of these findings, an alternative specification based on a structural identification of the model was tested, using a Cholesky decomposition, keeping in mind the mentioned limitations to this application. Results, shown in Figures A.2 and A.3 of the Online Appendix, are qualitatively similar to those presented here. The choice of exogenous variables to include in the model was also tested. Two proxies for the impact of supply bottlenecks on the global value chains that were prevalent over 2021 were considered: an indicator of the goods cost of shipping, the Baltic Dry index, and the manufacturing PMI delivery time indicator in the euro area, with no significant changes to results. An alternative version was estimated by replacing non-energy import prices by an aggregate of euro area farm gate prices, alongside the remaining goods deflator and the services deflator.[6] Given that food prices played an important role in recent inflationary pressures, the transmission of shocks for these items may have been different than for overall import prices. Results, available upon request, are qualitatively similar to those above described, with an increase in spillovers when the sample is extended to 2022 that takes place mostly trough food items. The main difference is that source effects increase with the extended sample for all components and become closer among core ones.

6. Data available at https://agriculture.ec.europa.eu/international/agricultural-trade.

To understand the importance of price spillovers over time, the analysis is extended by adding a time dimension. Figure 4 illustrates the importance of spillover effects on each category total variance after a shock in all components, computed using different horizons for the h-step-ahead forecasts. It should be noted that, in the first sub-sample, the importance of inflationary pressures is most pronounced in the first 9 months, with visible quarterly increases, while after the first year the weights become relatively stable. There is a clear difference when looking at the sample that includes the period with higher inflation. The steepening of the bars presented reflects not only stronger indirect effects across components but also a higher importance of price spillovers over time as the transmission of inflationary pressures is still relevant after 12 months. This result is extensive to most components, specially in the most affected: unprocessed and processed food and non-energy industrial goods. The aggregate of energy goods reports high increases in the first 6 months but then slows down. The exception is the category of services, which is the one that suffers less from inflationary pressures coming from the others, as, in reality, the weight of indirect effects decreases after the first year.

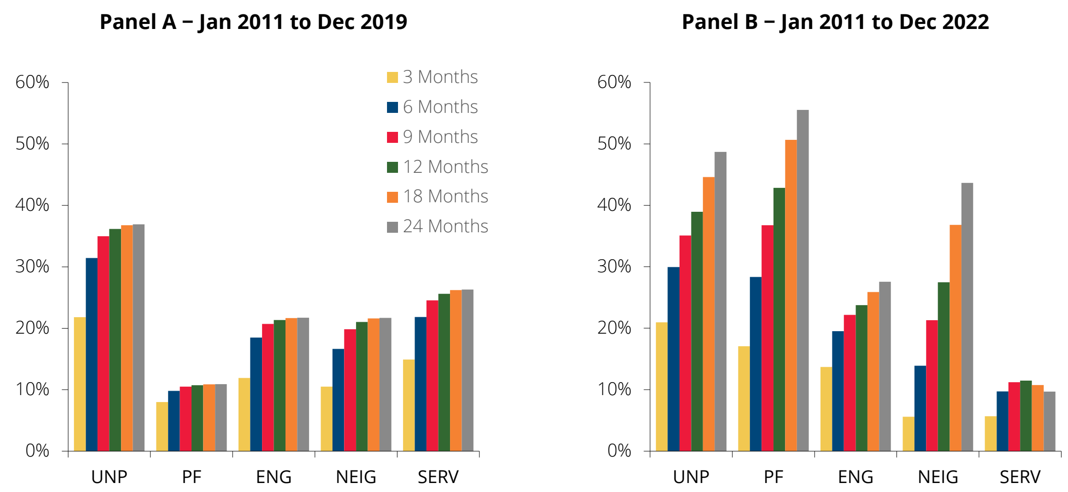

FIGURE 4: Importance of spillover effects on each component's variance | Percentage

Sources: ECB, Statistics Portugal and authors' calculations. Notes: The importance of spillover effects on the variance of each component is defined as the weight of spillover effects from that component in the total variance (sum of all elements of each line of the matrix in Figure 2). The measure is computed with GIRFs of different horizons: 3, 6, 9, 12, 18 and 24 months.

Finally, the index of total spillovers is computed for different horizons, as shown in Figure 5. It expresses the importance of spillovers on the overall variance of the forecast errors. The addition of the most recent observations leads to 5% and 13% increases in the weight of spillover effects in the first 12 and 24 months, respectively, while remaining constant at shorter horizons. This steepening shows again that spillovers are more important for a longer period, meaning that the rise in spillovers between the two sub-samples is not due to a higher contemporaneous correlation of relative price changes but rather to the transmission of those through the lag structure of the BVAR.

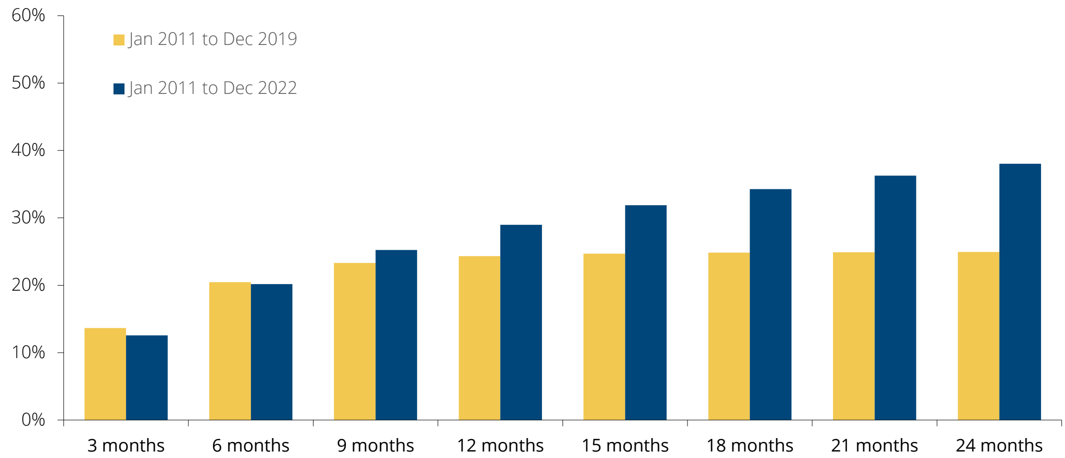

FIGURE 5: Index of total spillover effects over time | Percentage

Source: authors' calculations. Notes: The index of total spillover effects is the ratio between the sum of spillover effects and sum of all elements of the matrix in Figure 2.

2.4. *Upstream Spillovers*

As an extension, upstream price spillovers are investigated by including in the model the PPI, to assess the transmission of effects along the production value chain. Data pertaining to some subsectors is unavailable for the whole sample, as such it was replaced with the weighted average of the PPI of the remaining subsectors on the same aggregate. There are data availability issues as the sample of year-on-year rates of change starts only in Jan 2011.[7] Within the aggregate of consumer goods, the PPIs cover more directly the production of processed food and NEIG.[8] The aggregates considered in the model include: food, beverages and tobacco (PPI_PF), remaining consumption goods (PPI_CXPF), investment goods (PPI_INV), intermediate goods (PPI_INT) and energy goods (PPI_ENG). This order for the inclusion of variables in the model is an attempt to order them (increasingly) based on the average distance to final use, like in BIS (2022) and Antràs *et al.* (2012). Thus, consumption goods are the least upstream while energy goods are the most upstream, in the sense that energy is required to produce every other good. The exogenous variables are the same as in the previous subsection.

First, a model similar to the one described above was estimated with the PPI components alone. The results, available upon request, show that total spillovers have a magnitude close to the one obtained for the HICP model above. Price spillovers are reinforced for all items, except for non-food consumption goods, when considering the extended sample. In addition, HICP and PPI data were combined into a single BVAR model, using otherwise the same specifications of the previous subsection. Because of the limitations to degrees of freedom in estimation imposed by such a large number of

7. Price index data to construct the PPI related to food, beverages and tobacco is only available after 2010.

8. For a closer correspondence with consumer prices, consumption goods were separated into a food, beverages and tobacco aggregate and the remaining consumer goods, using detailed sector data and conversion tables available in the EU Commission Regulation No. 2020/1197 of 30 July 2020.

regressors, the lags of endogenous variables were reduced to three in this case. Some interesting results emerge as shown in Figure 6. In this model, total spillovers more than double when compared to those in the HICP or in the PPI models considered separately: around 25% for each of the individual models and 57% in the joint HICP-PPI model. Indirect effects coming from PPI components are in general stronger when compared to those of the HICP aggregates. The strongest and most pervasive effects steam from the processed food and intermediate goods PPIs (Appendix A.4). As regards HICP components, for the model estimated up to 2019, services have the strongest price spillovers, a large part of which due to effects on PPI components, possibly an indirect effect reflecting transportation costs, that was not possible to capture in the model with HICP categories only. When the sample period is extended to 2022, total spillovers increase from 57% to 63%. This reflects stronger transmission effects stemming from the majority of HICP components, in line with results from the previous subsection.

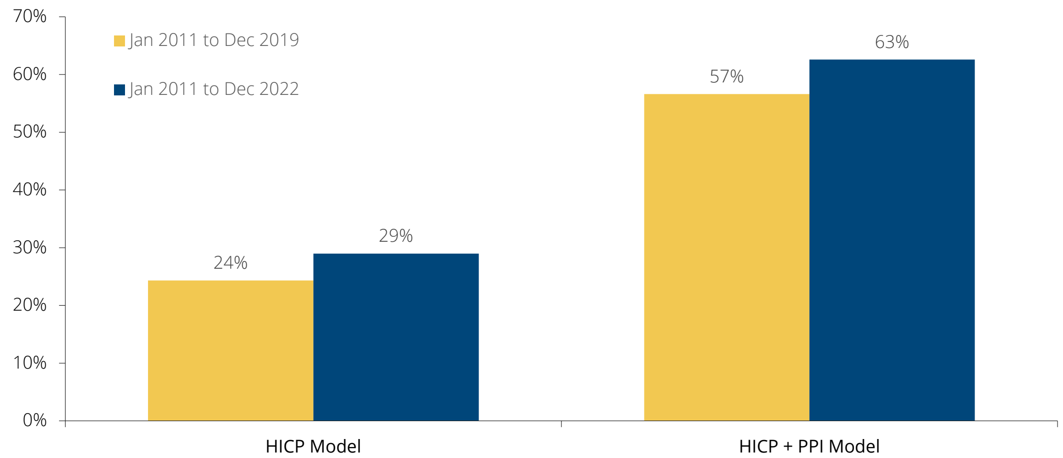

FIGURE 6: Index of total spillover effects for the HICP and HICP + PPI models | Percentage

Source: authors' calculations. Notes: The index of total spillover effects is the ratio between the sum of spillover effects and sum of all elements of the matrix in Figure 2.

3. Common Inflation

Now, the role of price spillovers on the recent generalization of inflationary pressures is analysed by estimating a dynamic factor model, similar to the one shown in Luciani (2020), and applying it to a detailed breakdown of HICP time series. This statistical model allows the identification of co-movements across a large number of prices, capturing the low-frequency component of inflation, defined as *common inflation*. This measure enables the distinction between the extent to which a change in prices is caused by shocks that affect a large share of items, as opposed to changes that are specific to individual items or errors in measurement.

3.1. Model Specification

Each month-on-month inflation rate in the dataset is decomposed into a common part χ_{it} and an idiosyncratic part ξ_{it}. Formally, if π_{it} is the month-on-month inflation rate, the following equality applies:

$$\pi_{it} = \chi_{it} + \xi_{it}. \tag{5}$$

Consider a panel of n disaggregated prices $\{\pi_t = (\pi_{1t}...\pi_{nt})' : t = 1, ..., T\}$, then:

$$\chi_{it} = \sum_{k=0}^{s} \lambda_{ik} f_{t-k}, \tag{6}$$

$$f_t = \sum_{l=1}^{p} \mathcal{A}_l f_{t-l} + u_t, \qquad u_t \overset{i.i.d.}{\sim} \mathcal{N}(0, Q), \tag{7}$$

$$\xi_{it} = \sum_{j=1}^{d_i} \rho_{ij} \xi_{it-j} + e_{it}, \qquad e_t \overset{i.i.d.}{\sim} \mathcal{N}(0, \Gamma), \tag{8}$$

where $f_t = (f_{1t}...f_{qt})'$ are the q common latent factors capturing co-movements across series and across time; $\lambda_{ik} = (\lambda_{i1k}...\lambda_{iqk})$ are the loadings for price i at lag k; $s \geq 0$ and $p \geq 1$ are finite integers; Q is a $q \times q$ positive definitive covariance matrix with full rank; the roots of $\mathcal{A}(L) = \sum_{p}^{l=1} \mathcal{A}_l$ and of $\rho_i(L) = \sum_{j=1}^{d_1}$ lie all outside the unit circle; and Γ is a $n \times n$ positive definitive covariance matrix with full rank. It must be noted that the common u_t and the idiosyncratic shocks e_t are assumed to be independent at all leads and lags.[9]

As in Luciani (2020), the proposed model is estimated using the Quasi-Maximum Likelihood method implemented through the Expectation-Maximization (EM) algorithm.[10] A measure of *common inflation* is computed using the estimated common components for each disaggregated price (χ_{it}) and the corresponding weight on the overall HICP (w_{it}). It is calculated as:

$$\pi_t^C = \sum_{i}^{N} w_{it} \chi_{it}. \tag{9}$$

3.2. Data and Estimation

The dataset includes data on 97 HICP subindices and corresponding weights, in accordance with the 4-digit COICOP classification. Those sub-indices not available since 2001 or that have been discontinued were replaced with the respective upper-level index. This resulted in a total of 75 items in the dataset. The raw monthly data, which covers the time period from 2001 to 2022, was obtained from Eurostat. Data was seasonally and calendar adjusted with X13 ARIMA procedures in Jdemetra+.[11] For the

9. For a rigorous treatment of this model, see Luciani (2020) and Barigozzi and Luciani (2019).

10. Further details on use of the EM algorithm in Dynamic Factor Models in Barigozzi and Luciani (2019).

11. This is the software for seasonal and calendar adjustment officially recommended by the European Commission to the members of the European Statistical System and the European System of Central Banks.

estimation, the number of factors q was set to 1 and the number of lags s in factors was set to 2. The same tests as in Luciani (2020) were performed. The Hallin-Liska information criterion was the method chosen for selecting the number of factors. The criterion is based on the behavior of the eigenvalues of the spectral density matrix of the factor loadings, which are a measure of the amount of variance explained by each factor in the model. In addition, the number of lags in the factor loadings, represented by s, was chosen such that the variance explained by the first r principal components of the covariance matrix of π_t is similar to the variance explained by the q principal components of the spectral density matrix of π_t (averaged over all frequencies).[12] All in all, the specification includes one common factor and each individual price can load the common factor in a time window of three months.

3.3. *Main Results*

Figure 7 shows the year-on-year percent change in the total HICP index, shown by the yellow line. The blue line represents the measure of *common inflation*, which is the year-on-year rate of change of the index obtained by aggregating the common component across all HICP items. It quantifies what total inflation at each month would be if idiosyncratic price shocks were absent over the previous 12 months.

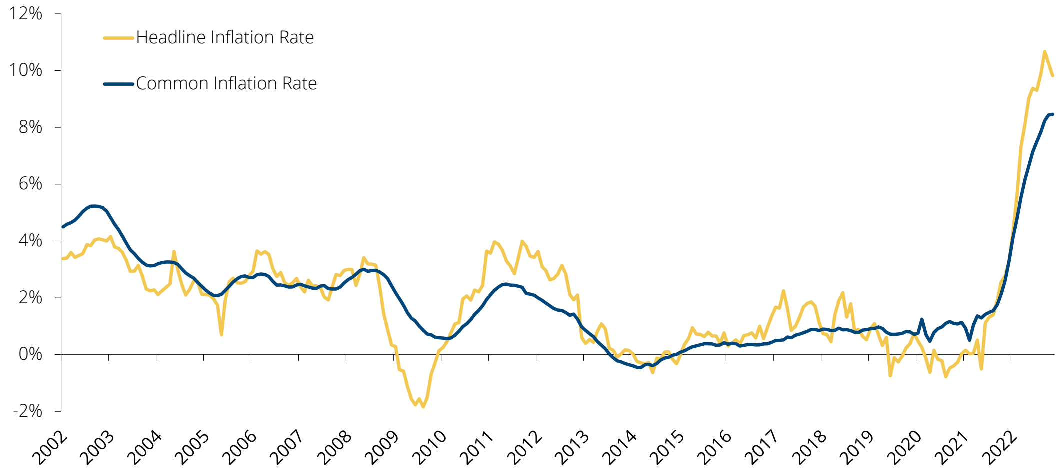

FIGURE 7: Headline and common HICP year-on-year rate of change | Percentage

Sources: Eurostat and authors' calculations.

The model suggests that headline and *common inflation* have generally moved in tandem over the past 20 years, with the exception of the period between 2008 and 2013. During this time, the Portuguese economy experienced significant macroeconomic shocks due to the Great Recession and the Sovereign Debt Crisis, which led to unique idiosyncratic dynamics. Prior to 2008, *common inflation* was around the inflation target of 2% set by the ECB, but after 2013, it remained closer to 0%. In an environment of low inflation, price changes in individual items are less transmitted to the remaining and thus to the aggregate price indices. In these periods, small and brief fluctuations in prices

12. This method builds on the work of D'Agostino and Giannone (2012).

occur around a relatively stable *common inflation*. This is in stark contrast to 2021 and 2022, during which both headline and *common inflation* surged above 8%, suggesting that a broad range of prices have increased simultaneously over this period. When inflation is high, increases in prices tend to be more aligned as the common component explains a larger share of the total variability of individual prices. Similar results were reported for the U.S. economy by Luciani (2020). The evolution of the computed *common inflation* measure compares reasonably well with other indicators of underlying inflation that belong to the toolkit of central banks (Appendix A.5). Even though all the measures aim to estimate the evolution of the (unobservable) persistent component of headline inflation, the *common inflation* helps to better understand the role of price spillovers on the recent generalization of inflationary pressures. Econometric techniques were used to filter out the transitory components of inflation by analyzing cross-sectional information across prices. Thus, this approach has the advantage of including the impact of medium-term shocks on food and energy, while excluding idiosyncratic fluctuations specific to core items.

To better understand the broad-based rise in prices, the exposure of HICP aggregates to common shocks in the recent years is investigated. For that, the common component of all sub-indices included in each of the main HICP components is combined, using the respective weights on the overall index. Figure 8 shows the contribution of each aggregate to the *common inflation* rate. The conclusion obtained is that the recent large external shocks caused soaring energy and food prices and the relative price changes in these components were transmitted to the remaining.

In the beginning of 2021, services were the highest contributors to *common inflation*, followed by food and energy goods. While the latter are more volatile, the former have historically been more affected by economy-wide fluctuations in prices. From mid-2021 onward, food and energy items have gained relevance in the dynamics of the *common inflation* and the two combined accounted for half of the broad-based variation of prices in January of 2022. After the beginning of the war, the bulk of the increase in *common*

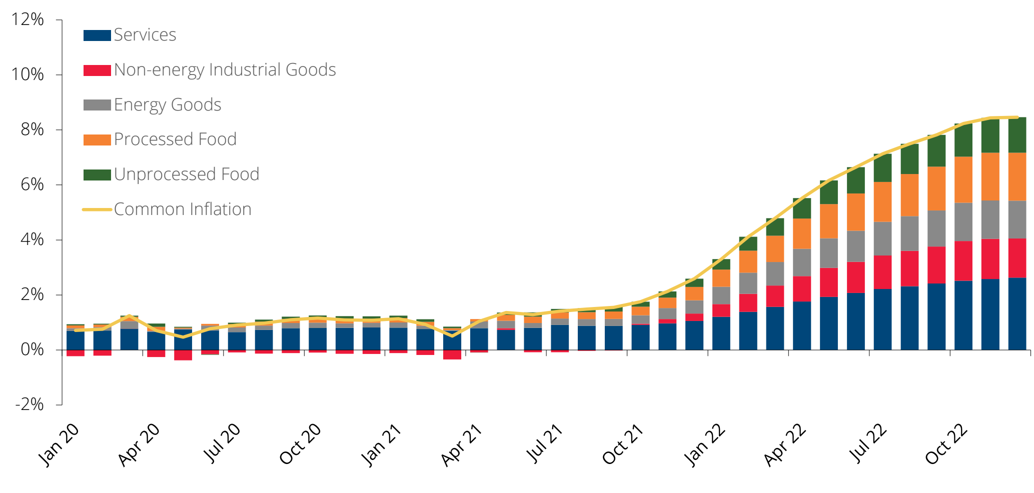

FIGURE 8: Contributions by HICP component to the *common inflation* rate | Percentage

Sources: Eurostat and authors' calculations.

inflation has been due to a broad-based rise in food prices, combing unprocessed and processed items, suggesting that they have increasingly co-moved with other prices. More than one-third of the overall increase of 8,5% is explained by the variation in the common component of the food (3%) and energy (1,3%) items. Currently, almost half of the increase in broad-based inflation is due to core items, that are more persistent and structural drivers of inflation. For example, NEIG prices, which in the past had very small contributions, picked up and since mid-2022 account for 1,4% of the total variation. This evidence suggests that the mentioned shocks may have induced stronger linkages across sectors and led to increased co-movement among prices, which is in line with the increase in price spillovers shown.

Comparing Figures 1 and 8, is it visible that over 2022, energy and food components have higher contributions to the headline HICP than to *common inflation*. This is in line with the fact that these components are the most volatile of the HICP. On the other hand, the contribution of services to *common inflation* is higher than in the headline up to 2022 and similar from them onward, possibly reflecting idiosyncratic demand impacts of the pandemic on services involving social interaction. Over 2022, the contribution of services to headline and *common inflation* is very similar.

Finally, the computation of the *common inflation* measure also has the advantage of allowing to approximate the impact of the large shock caused by the invasion of Ukraine by Russia on the co-movement of prices. To understand the impact that this event had on the inflation dynamics, its effects on *common inflation* were quantified on the basis of the methodology presented by Luciani (2020). The final estimate of *common inflation* after the shock is compared with the quasi-final estimate obtained by estimating the parameters before the shock. Doing that, the instabilities and unusual co-movements across individual prices that emerged with the shock are isolated. Let:

$$UkW_t^C = \chi_{t,Fin}^C - \chi_{t,Q-Fin}^C, \tag{10}$$

if $t \geq$ February 2022, otherwise is 0. $\chi_{t,Fin}^C$ corresponds to the *common inflation* indicator estimated with the full sample, while $\chi_{t,Q-Fin}^C$ corresponds to the quasi-final estimate of *common inflation*, obtained by estimating the parameters up to January 2022 and running the Kalman Smoother until December 2022. Figure 9 shows the evolution of *common inflation* in yellow and its decomposition between what *common inflation* would be if the parameters were kept unchanged after February 2022 and the increase in inflation due to the external shock caused by the invasion of Ukraine by Russia.

Since February 2022, the effects from the Ukraine Invasion have increasingly boosted *common inflation*, reaching a contribution of 3% in December. A detailed analysis of the contributions per component shows that food and energy were the most affected by the invasion of Ukraine. On the other hand, this shock had little impact on the rise of the common components of the the less volatile aggregates, i.e. NEIG and services.

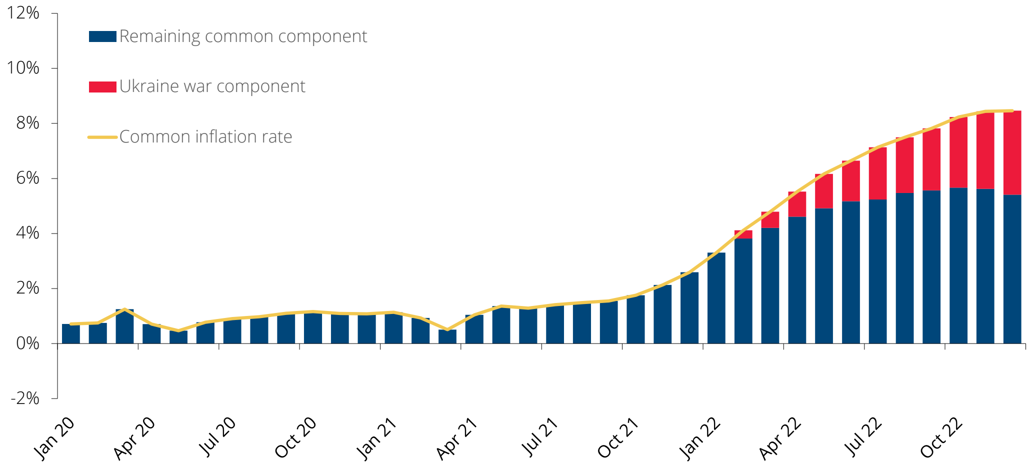

FIGURE 9: *Common inflation* and the impact of the war in Ukraine shock | Percentage

Sources: Eurostat and authors' calculations.

4. Final Remarks

Headline inflation has increased sharply in Portugal since mid-2021. Food and energy goods played a key role as drivers of the inflationary pressures but the great dynamism of their prices in the recent period was extended to the typically more stable categories. In this article, the role of price spillovers on the generalization of price increases is examined. First, a BVAR model with aggregate HICP data for Portugal is estimated to compute spillover measures, as in Borio *et al.* (2023), and compare a period with a low-inflation environment against the last years with the large price hikes. Price spillovers rose in the most recent period, meaning that idiosyncratic shocks in each component are transmitted more intensely through the production chain and have a greater impact on the price volatility of the others. The initial rise in raw material prices may have caused inflation of costs in the early stages of production, which then led to higher prices for goods and services throughout the production process. The higher magnitude and persistence of these effects suggest that relative price shocks are more likely to propagate to underlying inflation as they echo more into other components. For this reason, a measure of *common inflation* is constructed, as in Luciani (2020), which identifies co-movements across a large number of prices. As the most affected items have moved jointly with many others, the impact caused by the large external shocks has been converted into broad-based inflationary pressures.

Further avenues for research include analyzing more formally the properties of the common component of inflation as an underlying inflation indicator, in particular its forecasting performance and its behavior within a Phillips curve.

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