Aggregate price pressures along the supply chain: a euro area perspective

Teresa Messner, Thomas O. Zörner[1]
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In this article, we take a closer look at how price pressures affect sectoral and aggregate price indices. From a central bank perspective, especially, it is important to know how price changes on a more granular level affect the aggregate price index, which is often used as a benchmark to assess price stability. We employ a vector autoregression with a set of price and macro variables and perform an impulse response analysis. A simulation of a specific price shock enables us to trace its dynamic impact on a variety of price variables over time. Our main findings indicate that (1) sectoral price pressures impact both sectoral and headline inflation, and (2) the price pass-through increases at later stages of the production process, being nearly one-to-one for changes in producer prices. Moreover, (3) upstream and intermediate energy prices have the most sizable direct effect on sectoral variables by far, while food prices appear to be stronger determinants of headline inflation. In general, our results suggest that sectoral price developments can be indeed informative for headline inflation, confirming results of more complex network models.

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When companies face increases in their input prices (e.g. raw material, energy or intermediate goods prices), they may pass these cost increases on to their buyers. In case of an intermediary producer, it is likely that these increases will be passed on again to the next stage until, eventually, these costs reach the final consumers. Knowing how fast this process – the pass-through of costs along the supply chain to final consumers – evolves is of great importance to policymakers, enabling them to make quick and informed decisions. In particular, it is also crucial to know not only the evolution but also how much of the price increases is actually passed on at each stage of the supply chain, and whether there are sectoral differences. In this article, we estimate the effects of unanticipated changes in a variety of input prices higher up in the supply chain on consumer prices using a small-scale Bayesian vector autoregression.

Our main findings indicate that (1) sectoral price pressures impact both sectoral and headline inflation, and (2) the price pass-through increases at later stages of the production process and is nearly immediate for changes in producer prices. Moreover, (3) (upstream and intermediate) energy prices have by far the most sizable direct effect on sectoral variables, while food prices appear to be stronger determinants of headline inflation. In general, our results suggest that sectoral price developments can be indeed informative about the path of headline inflation,

[1] *Oesterreichische Nationalbank, Monetary Policy Section, teresa.messner@oenb.at and thomas.zoerner@oenb.at.* *Opinions expressed by the authors of studies do not necessarily reflect the official viewpoint of the OeNB or the Eurosystem. The authors would like to thank Christian Glocker (WIFO) for constructive comments that enhanced the quality of the article. Moreover, we thank the participants in the authors' workshop for Monetary Policy & the Economy Q4/22–Q1/23, a special issue on inflation, especially Fabio Rumler, Martin Schneider, and Gerhard Fenz (all OeNB) for valuable suggestions. Excellent research assistance was provided by Nico Petz (formerly OeNB).*

confirming results of more complex network models (e.g. Baqaee and Farhi, 2019; or Auer et al., 2019).

1 Motivation and literature

As different producers need different input, some may be more exposed to price increases than others. Quite recently, the ECB's benchmark to assess price stability, the Harmonized Index of Consumer Prices (HICP) for the euro area, showed a broad increasing pattern. Both headline inflation, including all HICP components, and core inflation, without volatile components such as food and energy, increased at an accelerated pace from end 2021 onward as seen in chart 1. In this article, we take a closer look into how price pressures affect sectoral and aggregate price indices in the euro area.

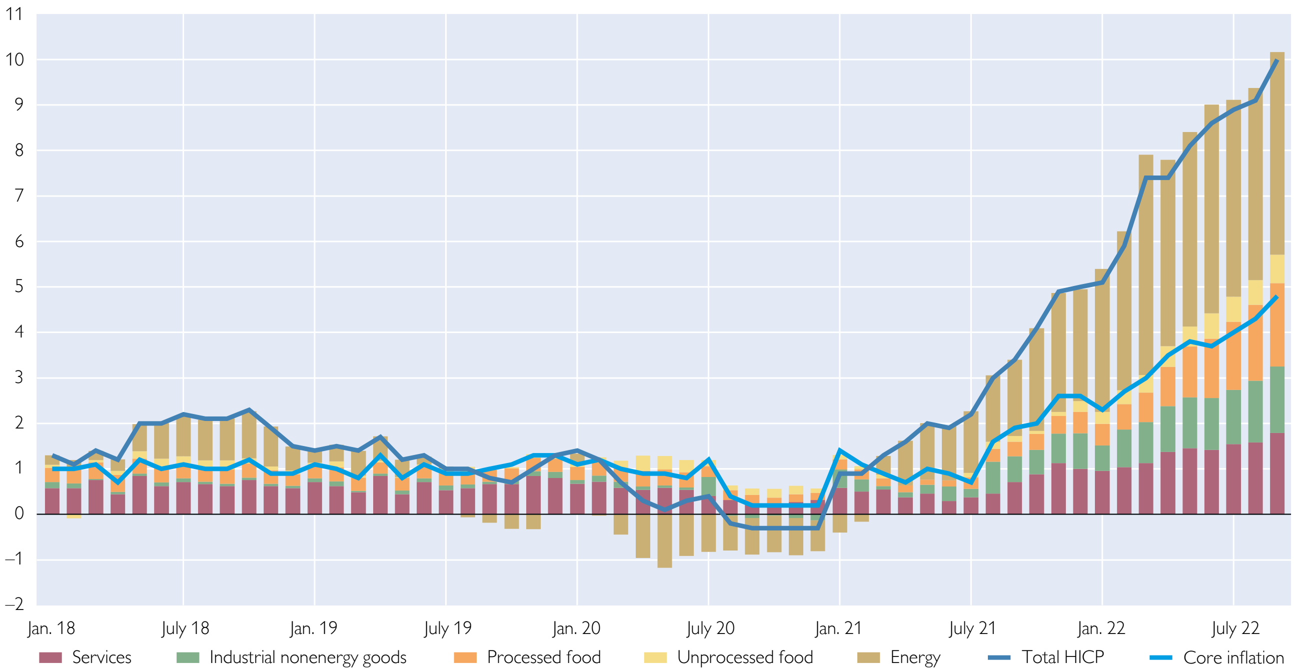
A broad body of literature has studied the role of price dynamics at the sectoral level, trying to disentangle the role of aggregate and local, i.e. sector-specific, shocks. In general, the literature attaches much weight on aggregate shocks as drivers of headline inflation volatility. However, there is also evidence that sectoral shocks determine sectoral inflation developments, while aggregate developments do not play a sizable role. The persistence of headline and sectoral inflation is, however, driven by aggregate factors (see, among others, Andrade and Zachariadis, 2016; Kaufmann and Lein, 2013; de Graeve and Walentin, 2015).

However, these studies appear to not fully address the complex sectoral interlinkages in firm networks. Firms may use and produce intermediate goods that

Chart 1

Euro area: HICP inflation rate and its components

Annual percentage change in %, contributions in percentage points



Source: Eurostat.

Note: Last observation: August 2022.

serve as input at later stages of the production chain, so when assessing the role of sectoral and aggregate shocks as determinants of inflation volatility and persistence, they may not be adequately disentangled (Foerster et al., 2011). More complex approaches make it possible to explicitly model and analyze the effects of price pressures at different sectoral stages. Globalization has made supply chains even more complex, with companies being woven into a tight network of suppliers and buyers (for a prominent example of such a modeling approach, see Baqaee and Farhi (2019) or Auer et al. (2019)). Modeling the *trickling down* of costs for any sequential input for every company involved in each sector of the economy requires, however, an intense effort of data work as demonstrated, for example, in Foerster et al. (2011) or Smets et al. (2018).[2] The latter find that differences in sectoral inflation persistence are to a large extent a result of sectoral differences in price stickiness, e.g. how fast prices of intermediate products can be adjusted and subsequently passed on. Furthermore, sectoral price pressures in different sectors along the supply chain can explain headline and disaggregate consumer price inflation volatility. This evidence would suggest that looking at sectoral price developments further up in the supply chain can be informative not only about sectoral consumer price inflation developments but also about headline dynamics.

In this article, however, we derive conclusions for consumer price changes in the euro area by looking at such supply chain pressures from an aggregate perspective. Such a perspective, i.e. "the broad picture", is necessary in the context of monetary policymaking as central banks in general focus on an aggregate price indicator. While our approach comes at some costs, we see three major advantages in the aggregate nature of our analysis. First, we rely neither on strong assumptions like, for instance, how to model nominal rigidities, nor on an explicit model stance about the underlying production networks. Second, we circumvent issues associated with the availability of data on distinct production linkages across the euro area. As mentioned above, missing data make the use of imputation techniques necessary, which ultimately may affect the reliability of the results. Finally, our analysis provides useful evidence for monetary policymakers, who base their decisions on aggregate price index developments.

In our empirical approach for unveiling aggregate price pressures along the supply chain, we estimate a small-scale Bayesian vector autoregressive (BVAR) model in the fashion of Giannone et al. (2015). For the identification of price shocks, we rely on sign restrictions proposed by Uhlig (2005). Our model predominantly pictures the aggregate supply side of the euro area economy at a monthly frequency. Based on our model estimation, we perform a simulation exercise by means of an impulse response analysis. More precisely, we simulate an unanticipated change of (1) aggregate freight costs and raw material prices (picturing price pressures at the "most upstream," i.e. initial stage of the supply chain) as well as (2) producer prices for food, energy and consumer goods (price pressures at the intermediate level in the supply chain) and trace their effects over time. The dynamics of the resulting impulse response functions (IRF) allow us (1) to gauge

[2] *There are challenges with respect to the treatment of micro price data due to measurement errors, sales and substitution effects (de Graeve and Walentin, 2015), which, taken together, may drive results in favor of aggregate shocks. Furthermore, there may be nonlinearities in how much intermediate prices can be adjusted. Once price pressures reach a certain extent, companies may be more likely to adjust prices considerably (see for example Nakamura et al., 2018).*

the dynamic effects of these particular shocks and (2) compare the shape and magnitude of the reactions of the HICP and its components across the sources of price pressures. In other words, we are interested in the speed and extent of how different price shocks feed into aggregate consumer prices over time.

2 Empirical strategy

Using macroeconomic data, we estimate the responses of aggregate consumer prices to price shocks further up in the supply chain. We want to know how large and how persistent the effects of such sudden shocks on consumer prices are. An example would be how downstream consumer prices react to a rapid increase in upstream crude oil prices or intermediate energy producer prices. Amid the discussion on aggregate- vs. sector-specific effects, as we showed in section 1, we compare the responses of the headline HICP to the responses of specific components of the HICP, such as energy prices.

Our small-scale empirical model sheds light on such macro reactions over time in the euro area as a whole. The empirical application investigates the effects of unanticipated changes in upstream prices in a small-scale hierarchical vector autoregression (BVAR) with a Bayesian stance of estimation.

Figure 1 gives an overview of the model specifications. Overall, we estimate eight models, with an identical set of variables differing only in the (eight) upstream and intermediate cost or price series. All variables are defined in terms of annual rates of changes in percent. For our analysis, we simulate a one-standard deviation shock. The size of the shock in percent can be found in the first column of table 2.

We analyze price pressures in three sectors: goods, energy and food. For price pressures in the *goods sector,* we employ a freight cost shock (change in the Baltic Dry Index as a composite proxy for upstream supply cost pressures) and a shock to consumer goods producer prices (PPI as a proxy for intermediate prices). As far as the *energy sector* is concerned, we model oil and gas price shocks and again an energy producer price shock. Lastly, for the *food sector,* we model a wheat price shock, an overall food commodity price shock and again a shock to food and beverages producer prices. We run these models twice, to estimate the effect on the *respective HICP components* (consumer prices of nonenergy industrial goods, energy and food and beverages including alcohol and tobacco) and on the *headline inflation* (HICP). The BVAR models are specified with 12 lags and use monthly data spanning from December 2001 to February 2020, intentionally excluding the

Figure 1

Simple schematic depiction of sectoral prices along the supply chain

Goods sector	
Freight costs	Baltic Dry Index
Producer prices for consumer goods	PPI
Consumer prices for goods	HICP
Headline inflation	HICP
Energy sector	
Crude oil price	Brent in USD
Natural gas price	S&P GSCI commodity index
Producer prices for energy goods	PPI
Consumer prices for energy	HICP
Headline inflation	HICP
Food sector	
Food commodity prices	HWWI commodity index
Wheat price	S&P GSCI commodity index
Producer prices for food, beverages	PPI
Consumer prices for food, beverages	HICP
Headline inflation	HICP

Source: Authors' compilation.

pandemic period with its pronounced volatility in almost all aggregate variables.[3] A formal representation of the model we use can be found in the appendix.

While the Bayesian approach proves useful in macroeconomic applications where data are usually scarce, the prior choice may be a crucial issue. However, by using the hierarchical approach proposed by Giannone et al. (2015), we opt for a data-based elicitation of our priors. As laid out in Kuschnig and Vashold (2021), who implemented this flexible approach in a convenient R routine, the subjectivity of prior choices and the associated uncertainty is thus alleviated. We identify the shocks through sign restrictions following Uhlig (2005); our specific restrictions can be found in table 1. In this table, + (–) indicates a positive (negative) on-impact reaction of a certain variable to the specific shock, while a blank cell refers to no a priori impact restriction.

Along the lines of Smets et al. (2018), as discussed in section 1 and indicated in the first column of table 1, we assume that all (positive) cost and price shocks will (eventually) push up HICP headline inflation. Apart from differences in price stickiness across sectors, the weights with which the sectoral price indices feed into the headline HICP may also impact the extent to which sectoral shocks determine headline inflation. After services (2022 weight: 42%), goods have the largest weight in the euro area HICP (26%), followed by food (21%) and energy (11%).

As indicated in the subsequent columns in table 1, we assume that (positive) sectoral price shocks result in increases in sectoral inflation. In other words, we assume freight cost, commodity, and PPI price shocks to directly impact the specific sectoral components of HICP inflation. A shock to freight costs and goods PPI prices will thus directly impact consumer goods prices (column 2). Likewise,

Table 1

Sign restrictions in BVAR

	Shock on					
	Variables					
	HICP headline	HICP goods	HICP energy	HICP food	HICP services	Industrial production
Shock of	*Annual rate of change*					
Baltic Dry Index	+	+	+	+		–
Consumer goods PPI	+	+				–
Brent crude price (USD)	+		+		+	–
Natural gas price index	+		+		+	–
Energy PPI	+		+			–
Food raw material price index	+			+		–
Wheat price index	+			+		–
Food and beverages PPI	+			+		–

Source: Authors' compilation.

Note: A (+) indicates a positive reaction on impact of the respective variable in the system, while (-) corresponds to a negative reaction. Blank cells () denote no a priori restriction. The restrictions are imposed for one month.

[3] *This is a common procedure when dealing with the extraordinary dynamics during the COVID-19 pandemic as shown in Lenza and Primiceri (2022). However, to ensure robustness, we reestimated the models for the full sample, ranging from December 2001 to December 2021. The results are qualitatively very similar but exhibit a larger uncertainty due to the pronounced volatility. To conserve space, the results are available from the authors upon request.*

a shock to energy PPI contemporaneously positively impacts HICP energy prices (column 3). The same logic also applies to an unexpected increase in food commodity prices that results in a direct increase in HICP food prices (column 4). The latter has been shown, inter alia, in Baumeister et al. (2014), who find evidence for effects of food commodity price shocks on retail food prices. However, the effects are apparently more prevailing in developing countries. Likewise, Peersman et al. (2021) document an increasing impact of oil prices on food commodity prices since the 2000s. In addition, they also find a reverse relationship between a shortfall of global food commodities and oil prices.

Furthermore, our restrictions assume that freight costs and energy price shocks also affect other components of HICP inflation, as discussed in Kilian (2008). Unexpected freight cost increases are also expected to impact food and energy HICP prices (columns 3 and 4) but not services, while energy price increases are assumed to affect only services and energy prices but not goods or food prices. This is motivated by findings of Baumeister et al. (2014), who document no link between oil prices and increases in food processing costs or food retail prices in the USA. Finally, as shown in the last column of table 1, all shocks are assumed to impact industrial production negatively, such that our shocks carry the notion of supply-side distortions in contrast to demand-specific shocks.

3 Results

In this section, we discuss the results of our empirical strategy and the simulation of a one-standard deviation shock according to table 1. We start with the direct effects on a sectoral level with inflation components and continue with a more aggregate view on headline inflation. Each chart in each panel depicts the dynamic evolution of the respective variable over 50 months after the shock as an impulse response function. After this period, almost all variables have returned to their mean. A numeric summary of our key results can be found in table 2. To conserve space, we only report selected impulse response functions and will provide the remaining results upon request.

3.1 Sectoral (direct) effects

In the left panel of chart 2, we show the shock responses, while the right panel shows the relevant component of the HICP, such as goods, energy and food.

As for the goods sector (chart 2, top panels), both the freight cost and PPI price shocks show a rather similar pattern (left panel), while the magnitude of the shock in percent is far more pronounced for the more volatile freight cost series (77% year on year) than for the PPI price series (0.6% year on year) as seen in table 2.[4] The reaction of consumer goods inflation to the shocks (right panel) is also similar, with goods price inflation increasing by 0.6 percentage points on impact of the freight cost shock and by slightly more, namely 0.9 percentage points to the PPI goods price shock. The comparably modest response can most likely be linked to final consumer goods consisting in different intermediate goods, which results in a very heterogenous supply chain structure that potentially offsets idiosyncratic

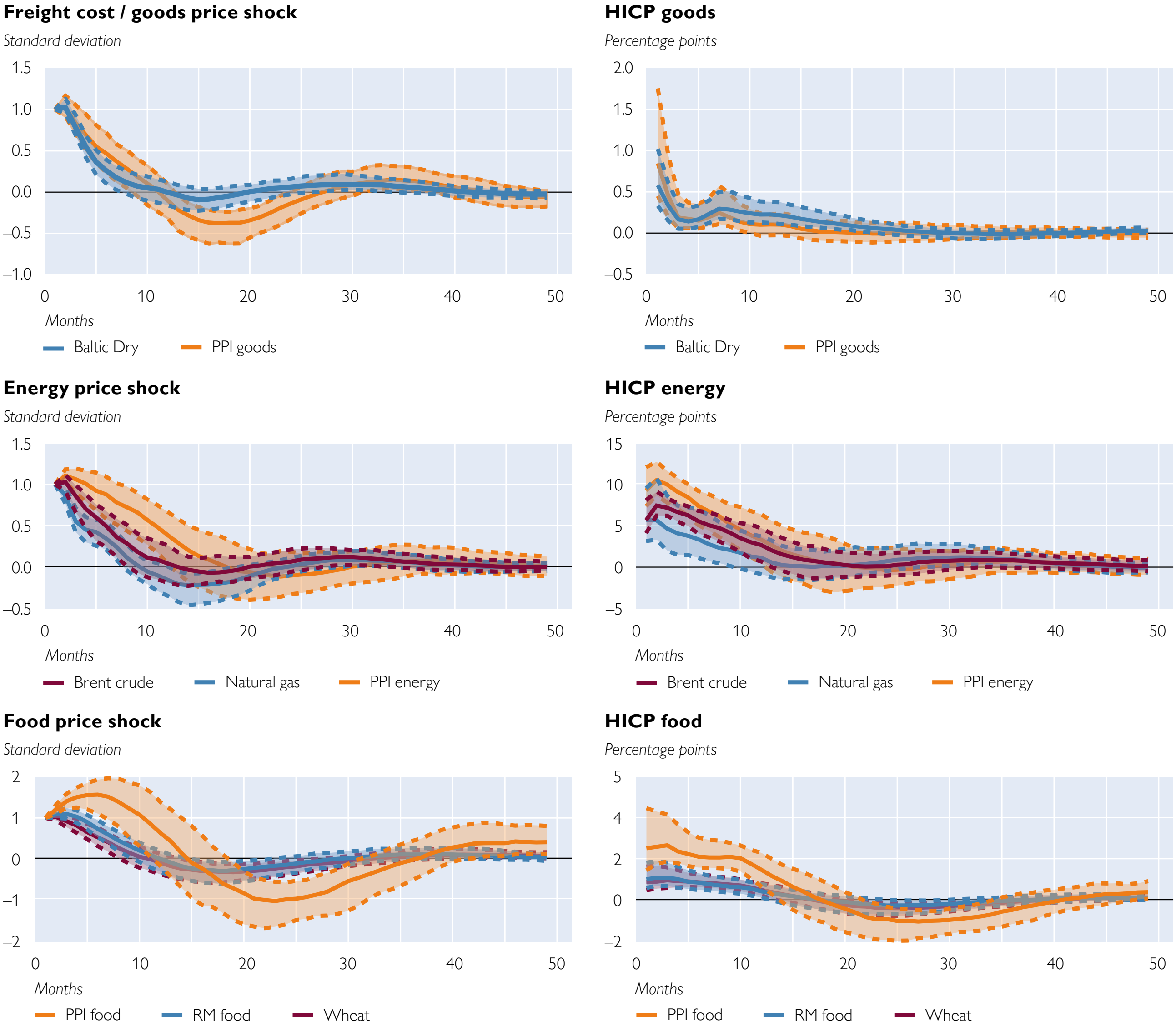
[4] *In general, disentangling a freight cost shock (based on the Baltic Dry Index) from an energy shock (based on the crude oil price) is not an easy task. Following the reviewer's suggestions, we thus re-estimated the effect of a freight cost shock with an augmented variable set that contains the crude oil price. By not imposing any restriction on it, we may infer the nature of the freight cost shock in the reaction of our oil price series. The results are qualitatively very similar to our main specification.*

distortions. Both series swiftly return to their mean, even though the impact of the supply cost shock remains significant twice as long as the PPI shock. As a result, the effect of the freight cost shock is rather long lasting and twice as large as the PPI shock in cumulative terms.

For energy price inflation (chart 2, middle panels), we observe that the shocks triggered by an oil and natural gas price change or shocks triggered by a PPI change reveal subtle differences (left panel). The direct impact on HICP energy price inflation is quite sizable (right panel). On impact, the energy price inflation jumps up by 5 to 9 percentage points. The impact of natural gas prices amounts to 5.4 percentage points (with sizable confidence intervals) and is the least persistent one

Chart 2

Impulse response functions of sectoral inflation



Source: Authors' compilation.

Note: The chart shows impulse response functions of the components of HICP inflation for several shocks in the goods, energy and food sectors. PPI refers to the relevant producer price index. The solid lines correspond to the posterior median of a one standard deviation shock, while the shaded areas refer to the 68% credible sets.

(around 11 months). Given its uncertainty, it might however not be significantly different from the other shocks. This uncertainty surrounding the estimates is most likely due to the nature of our gas price series, which is an index figure that reflects *global* production and the market performance of natural gas contracts (futures).[5] The European natural gas market is a rather local market, consisting of different suppliers and network access. In contrast to crude oil, which is traded globally and therefore has a global price, the price for natural gas in Europe is not determined by one market.[6] Furthermore, gas prices feed into the HICP energy prices less directly (e.g. via heating or electricity prices) than oil prices, for which there is an almost direct link via fuel prices. In addition, it is likely that there are national policies in place shielding consumer prices from direct wholesale price changes.[7] The black line in this panel also shows that the impact of the PPI shock is the largest one (8.5 percentage points) and feeds into HICP energy inflation almost one-to-one, indicating an almost perfect pass-through. The shock persists for about 13 months and hence for about the same period of time as the one for crude oil prices. Taken together, this suggests that changes in the PPI for energy products, such as refined energy products like fuels, feed almost directly and rather persistently into HICP inflation, which is in line with evidence presented by Blair et al. (2017). This leads to a substantial cumulative impact on HICP energy prices.

In the case of food, we similarly conclude from the bottom panels of chart 2 that commodity price changes have a considerably smaller impact on HICP food prices (only around 1 percentage point on impact, illustrated by the purple and blue lines) compared to intermediate producer prices (about 2.5 percentage points

Table 2

Summary of our results

Shock	One standard deviation	Variable	Effect on impact	Duration	Cumulative effect	Variable	Effect on impact	Duration	Cumulative effect
	%		*Percentage points*	*Months*	*Percentage points*		*Percentage points*	*Months*	*(in pp)*
Baltic Dry	76.7	HICP goods	0.6	23	4.5	Headline HICP	0.4	18	3.8
PPI goods	0.6		0.9	10	2.7		0.4	4	0.9
Natural gas	38.2	HICP energy	5.4	11	39.0		0.3	8	1.7
Brent crude	33.7		5.6	14	64.5		0.4	13	3.6
PPI energy	10.0		8.5	13	84.0		0.6	11	4.1
Raw materials food	15.8	HICP food	1.0	13	9.8		0.4	18	5.2
Wheat price	29.9		0.9	14	10.0		0.4	20	6.4
PPI food	2.7		2.5	14	27.9		1.1	19	16.5

Source: Authors' compilation.

Note: This table depicts the key results of our IRF analyses in section 3.1 and 3.2. The first column shows the shocks and column 2 the size of the one standard deviation shock in percent (annual rate of change). Column 3 refers to the HICP component affected by the shock, column 4 shows the effect (posterior median) on impact in percentage points, column 5 shows the duration until the shock turns insignificant (i.e. the lower standard interval crossing zero) in months. The last column shows the cumulative effect of the shock in percentage points over the duration specified in the previous column. The remainder of columns show the same for headline inflation instead of for individual HICP components.

[5] *The specific price series is the S&P GSCI Natural Gas Index. In addition, we checked for different series associated with natural gas, resulting in similar reactions of HICP energy prices.*

[6] *An overview of the important pipelines and storage facilities in Europe can be found via https://transparency.entsog.eu/#/map.*

[7] *Bruegel provides an overview and data of national policies limiting the impact of wholesale energy prices for consumers.*

on impact as shown by the black line). This might also be the result of the different origins of the shocks, with commodity prices being global variables whereas the PPI data are European. As suggested by Ferrucci et al. (2010), the Common Agricultural Policy (CAP) in the European Union may be responsible for the muted impact of food commodity prices on HICP food prices. Both effects level out after about a year.

Hence, these results indicate that the cost pass-through increases at later stages of the production process and is close to be one-to-one for changes in producer prices. This might be due to different market power or contract characteristics in earlier stages of the supply chain as indicated by Gaudin (2016) or Duso and Szücs (2017).[8]

3.2 Aggregate effects

Rerunning the estimations for headline inflation, which includes more volatile elements like energy and food, we observe a striking feature. As seen from chart 3, all sector-specific shocks significantly impact headline inflation in the euro area. However, the effect on headline inflation is substantially smaller compared to the direct sectoral impact. We conclude here that unexpected increases of energy prices, producer prices, food prices and transport cost are reflected only to a smaller extent in the aggregate measures. However, the aggregate nature of our analysis may mask sector-specific heterogeneities in line with Foerster et al. (2011). This includes sectoral differences in price adjustment, substitution effects and the effects of the weights that each component receives, potentially resulting in a less pronounced reaction of headline inflation or even different inflation regimes (see e.g. De Fiore et al. (2022) for a very recent discussion).

Interestingly, the initial impact of freight cost and PPI goods price increases on headline inflation (chart 3, top right panel) is rather muted at 0.4 percentage points despite the large weight attached to goods in the HICP. In line with Furceri et al. (2022), additional freight costs, however, may feed into aggregate HICP inflation rather persistently. Our analysis suggests that the effects may last for about one and a half years. During this period, the supply cost shocks could add almost 4 percentage points to headline inflation. Furceri et al. (2022) argue that import intensity determines the size of the impact of freight cost increases on HICP inflation and the monetary policy regime the duration of the impact.

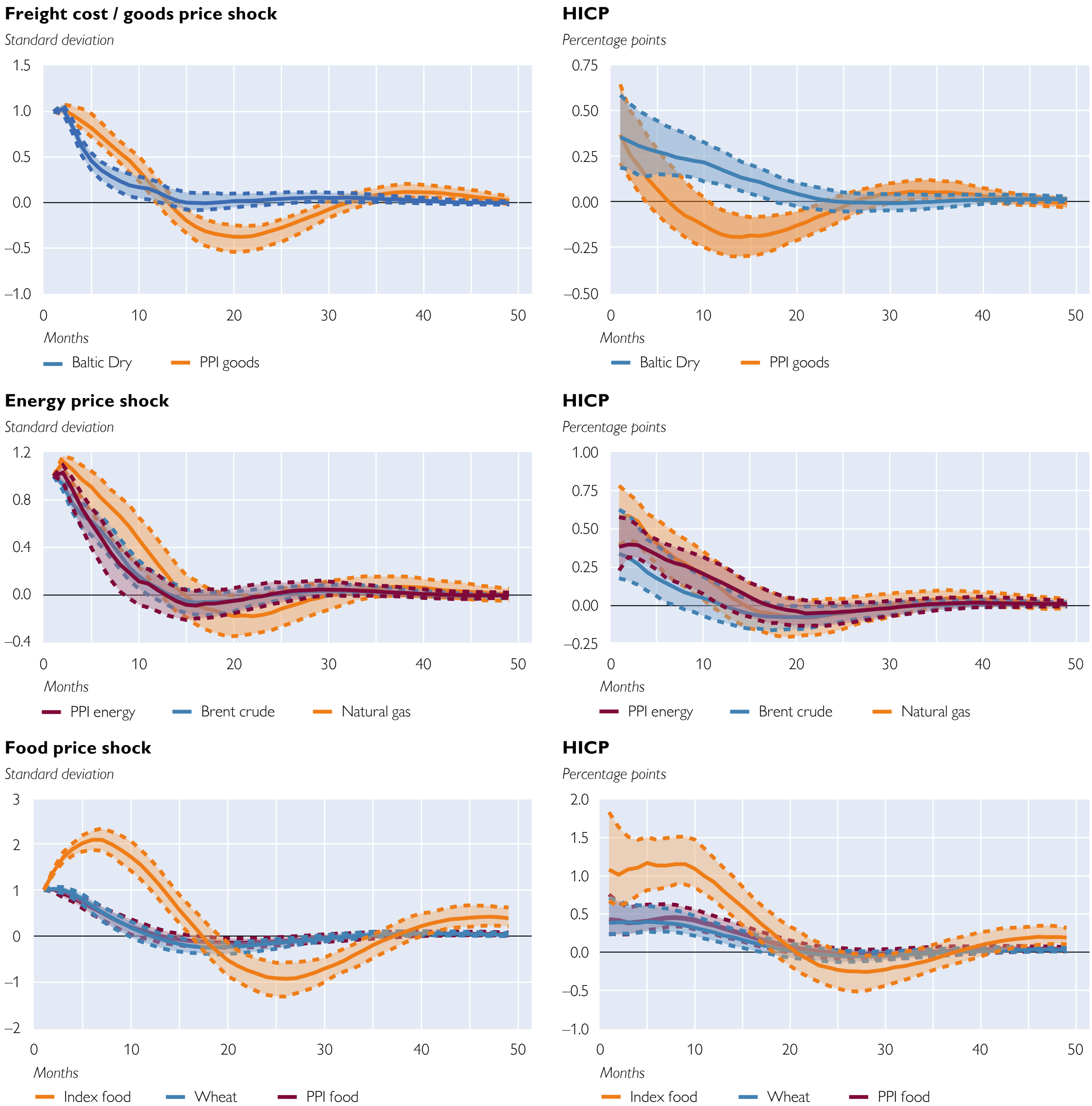
As for upstream and intermediate energy prices, we observe largely the same patterns as for the direct, sectoral responses. In terms of size, however, the reaction of headline inflation to energy prices, which receive a smaller weight in the HICP compared to goods or food items, remains low at 0.3 percentage points to 0.6 percentage points on impact, as can be seen in the middle right panel.

Lastly, food prices further downstream again seem to play a more prominent role for headline inflation (bottom, right panel) than those further up, accounting for 1.1 percentage points compared to 0.4 percentage points on impact. Sizable distortions in producer prices for food (including e.g. processed rather than unprocessed food) can thus lead to strong (cumulative) price increases in headline inflation (see also Ferrucci et al., 2010).

[8] *The Bureau of Labor Statistics provides a Handbook on how firms can deal with price adjustment (escalation) clauses in long-term sales and purchase contracts using the producer price index.*

Chart 3

Impulse response functions of headline inflation



Source: Authors' compilation.

Note: The chart shows impulse response functions of the components of HICP inflation for several shocks in the goods, energy and food sectors. PPI refers to the relevant producer price index. The solid lines correspond to the posterior median of a one standard deviation shock, while the shaded areas refer to the 68% credible sets.

4 Conclusions

In this article, we employed a small-scale model of the euro area's supply side to analyze the question of how a variety of price shocks affect the sectoral and aggregate evolution of price indices. For the euro area, our impulse response analysis shows that sectoral price pressures impact both sectoral and headline inflation. Moreover, the price pass-through appears to increase at later stages of the production process, being nearly immediate for changes in producer prices. Finally, energy prices have by far the most sizable direct effect on sectoral variables while food prices appear to be stronger determinants of headline inflation. In general, our results suggest that sectoral price developments can be indeed informative about headline inflation developments in the euro area. Thus, our analysis reveals the importance of idiosyncratic sector-specific shocks and suggests that a considerable amount of heterogeneity within the sectors may have aggregate implications. However, due to the characteristics of the euro area, our approach may mask a nonnegligible degree of heterogeneity across the individual member countries. A more granular analysis might reveal country-specific price pass-throughs. However, as a detailed analysis would go beyond the scope of this article, we leave this analysis for further research.

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Appendix

Our BVAR consists of the following vectors of observed variables that are given by $y_t^1 = \left[P_{i,t}^{Upstream},\ P_t^{Good},\ P_t^{Energy},\ P_t^{Food},\ P_t^{Service},\ IP_t \right]'$ for the inflation components, and $y_t^2 = \left[P_{i,t}^{Upstream},\ P_t^{Headline},\ IP_t \right]'$, for the headline inflation with $i \in \{Freight,\ PPI^G,\ Oil,\ Gas,\ PPI^E,\ ComFood,\ Wheat,\ PPI^F\}$, all defined as annual rate of change in percent. Thus, our vector autoregressive model reads

$$y_t^j = \sum_{p=1}^{12} A_p y_{t-p} + \epsilon_t,$$

where $j \in \{1,2\}$, A_p is a coefficient matrix associated with lag p and the error term $\epsilon_t \sim N(0, \Sigma)$ with variance-covariance matrix Σ.