MONITORING AND FORECASTING FOOD PRICES IN THE EURO AREA

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Abstract

This paper presents a comprehensive framework developed by the Banco de España to monitor and forecast food price dynamics in the euro area, particularly in response to the sharp increase in food inflation observed between 2022 and 2024. The study introduces a suite of models tailored to different aspects of the food value chain, integrating data from consumer and producer prices, farm-gate prices and international commodity and futures markets. Key tools include a Food Value Chain Model (VARx) to estimate the pass-through of commodity and fuel price shocks to consumer prices, an Asymmetric Price Transmission Model to capture non-linear effects and a Conditional Forecasting framework using different modelling approaches and futures data to simulate inflation scenarios. Additionally, a Vector Error Correction Model (VECM) assesses the long-term relationship between food and non-food prices. These tools aim to enhance central bank decision-making and food security analysis by providing timely, scenario-based insights into food inflation trends.

Keywords: food prices, food inflation, inflation, euro area, monitoring, forecasting, central bank.

JEL classification: E31, C53, Q11.

Resumen

Este documento presenta un sistema desarrollado por el Banco de España para monitorizar y prever la inflación de los alimentos en el área del euro, en respuesta al fuerte aumento de la inflación alimentaria observado entre 2022 y 2024. El estudio introduce un conjunto de modelos enfocados en diferentes aspectos de la cadena de valor alimentaria, integrando datos de precios de consumo y de producción, precios en origen (a pie de granja), así como de los mercados internacionales de materias primas y de futuros. Las herramientas clave incluyen un modelo de cadena de valor alimentaria (VARx) para estimar la transmisión de las perturbaciones en los precios de las materias primas alimentarias y de los combustibles a los precios de consumo; un modelo de transmisión asimétrica de precios para captar efectos no lineales, y un sistema de previsión condicional que utiliza diferentes opciones de modelización y datos de futuros para simular escenarios de inflación. Además, un modelo vectorial de corrección de errores (VECM) evalúa la relación a largo plazo entre los precios de los alimentos y los de otros bienes. Estas herramientas tienen como objetivo mejorar tanto la toma de decisiones de los bancos centrales como el análisis de la seguridad alimentaria, proporcionando información oportuna y basada en escenarios sobre las tendencias de la inflación alimentaria.

Palabras clave: precios de alimentos, inflación de alimentos, inflación, área del euro, seguimiento, previsión, banco central.

Códigos JEL: E31, C53, Q11.

Contents

1 Introduction

The world economy has witnessed sharp increases in food prices in recent years, driven by economic disruptions such as global supply shocks and climate-related events. In the euro area, food inflation surged markedly between 2022 and 2024, raising concerns among policymakers due to the substantial weight of food in the consumer price index and its potential impact on inflation expectations (see Figure 1). Between early 2021 and May 2025, food prices in the euro area rose dramatically —driven by global commodity shocks— with inflation peaking in March 2023 at 15.5% and affecting nearly all food categories; cereals, meat, and dairy were the largest contributors, and by that point, 93% of food items in the HICP basket showed historically high inflation rates. Price levels surged across the board: food became 29.4% more expensive in the euro area and 33% in Spain compared to January 2021, with oils and fats rising by 56% in the euro area and 65% in Spain, and other staples like dairy, sugar, and coffee increasing between 30% and 46%.

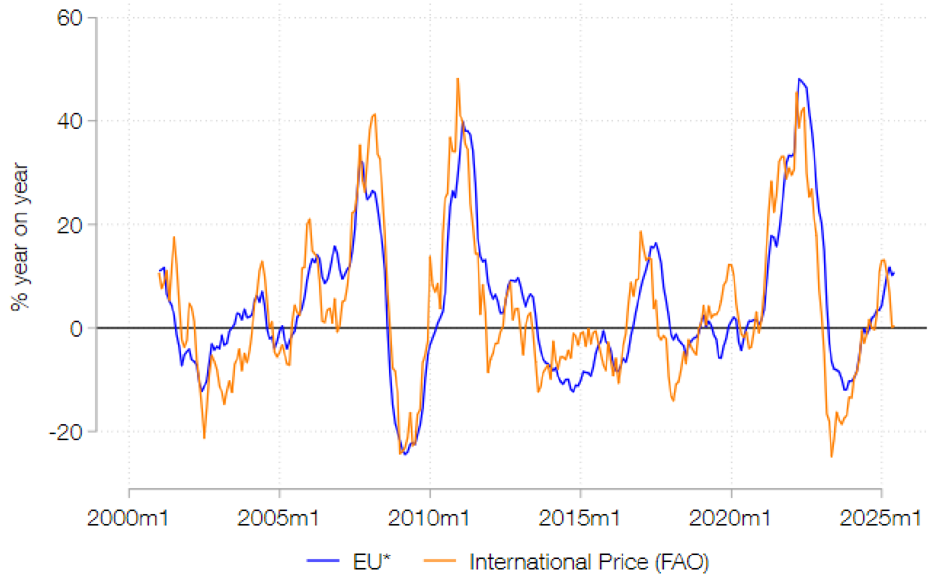
In response to the sharp and widespread rise in food prices across the euro area during the 2022–2024 inflationary crisis, the Banco de España developed a suite of analytical tools to monitor and forecast food inflation, which had a significant impact on headline inflation, especially in countries like Spain. These models, each targeting a specific aspect of food price behavior, draw on extensive datasets covering consumer, producer, and commodity (farm-gate) prices to ensure all major cost drivers are considered. This report aims to make these internal tools accessible to a broader audience by detailing their methodologies and key insights, thereby supporting ongoing surveillance of food inflation and enhancing decision-making in monetary policy and food security analysis.

The paper is organized as follows. In Section 2 we describe the data used in this study. In Section 3, in turn, we present the following models and their applications:

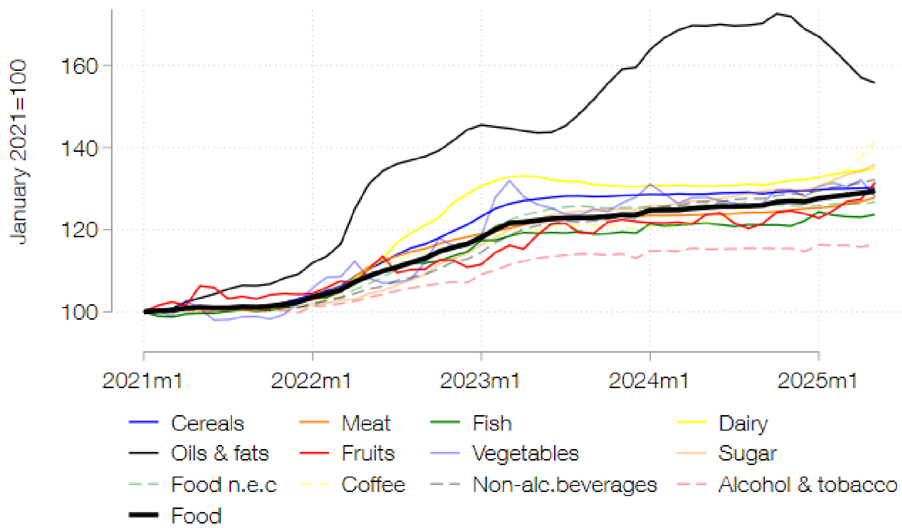
- Food Value Chain Model (Section 3.1): A vector autoregression (VARx) model to quantify how shocks in agricultural commodity prices and fuel costs propagate through the food supply chain to consumer prices. It provides estimates of the pass-through effect at different stages of the value chain: from farm-gate prices to producer prices to retail prices.

Figure 1: Food price developments

(a) Evolution of food commodity prices: International vs. European trends



(b) Evolution of food consumer prices in the euro area



Sources: DG-Agri Eurostat, FAO, IMF, World Bank, Refinitiv-Datastream and own calculations.
(*) The European Union (EU) aggregate is a weighted sum of selected food categories for direct comparison with the FAO International Food Commodity Price Index. The weights reflect each category's importance in the Harmonised Index of Consumer Prices (HICP) and are normalized to sum to one, since not all HICP food components are included: cereals (29%), dairy and eggs (22%), oils and fats (6%), meat (33%), and sugar (10%). These selected categories align with those used in the FAO index.

- Asymmetric Price Transmission Model (Section 3.1.2): An extension of the aforementioned VARx approach that allows for non-linear effects, distinguishing between food commodity and fuel price increases and decreases. It assesses whether food consumer prices respond differently to rising food commodity and energy prices than to falling prices, revealing asymmetric inflationary pressures in the euro area.

- Conditional Forecasting (Section 3.2): A scenario-based tool that uses the above models to project future food inflation under certain assumptions. For instance, it incorporates commodity futures prices to condition short-term forecasts, allowing analysts to simulate how anticipated movements in commodity markets (like expected increases in wheat or oil prices) could influence consumer food inflation in the coming quarters. This framework can be adapted to explore various scenarios, such as supply shocks or policy changes, and their potential impact on food prices.

- Long-Term Equilibrium Model (Section 3.3): A vector error correction model (VECM) which examines the long-run relationship between food prices and other consumer prices. It evaluates the persistence of food price changes by determining if and how food prices eventually revert to a stable equilibrium relative to non-food prices. It helps identify structural shifts – for example, a post-2022 shift suggesting that food prices may remain elevated relative to other goods.

Finally, in Section 4 we provide some concluding remarks.

2 Data

To effectively monitor and forecast food price dynamics in the euro area, we construct a harmonized and comprehensive dataset that integrates multiple sources and methodologies. Our objective is to develop models for each of the main food categories included in the Harmonised Index of Consumer Prices (HICP) for food, alcohol and tobacco, corresponding to ECOICOP groups 01 and 02. These groups serve as the reference classification for "Food" in the European Central Bank's quarterly projection exercises. The dataset is used consistently across all models presented in this report, and is detailed in Table 1.

We collect monthly data from Eurostat on harmonized consumer food prices (HICP) and producer food prices (PPI), both at the aggregate level and disaggregated across the 12 main food groups. These groups include: bread and cereals, meat, fish, dairy and eggs, oils and fats, fruits, vegetables and legumes, sugar and related products (e.g., jam, honey, chocolate), food products not elsewhere classified, coffee (including tea and cocoa), non-alcoholic beverages, and alcohol and tobacco. Where PPI data are unavailable for certain categories (e.g., non-alcoholic beverages), we construct aggregates from their subcomponents (e.g., mineral water and juices). Additionally, we compute an aggregate of non-food HICP components, which is used in Section 3.3.

Beyond consumer and producer prices, we incorporate a broad set of commodity price indicators. At the domestic EU level, we obtain farm-gate prices (what the farmers receive for their products) for cereals, dairy, olive oil, meat, and sugar from the European Commission (DG AGRI). These are complemented by international commodity prices from the International Monetary Fund (IMF) for items such as coffee, rapeseed oil, and soybean oil, and from the World Bank for tobacco. For sunflower oil of European origin, we use data from the Hamburg World Economic Institute (via Refinitiv Workspace).

To include forward-looking indicators, we integrate futures market data for key agricultural and energy commodities. These futures, sourced from major international exchanges, cover commodities produced within the EU or imported from major trading partners. Specifically, we use futures prices for milling wheat and rapeseed (from MATIF, continental Europe's primary agricultural derivatives market), white sugar (from LIFFE), Arabica coffee (from Brazil's BMF, reflecting Brazil's role as the EU's main coffee supplier), lean hogs and nonfat dry milk (from CME), and Brent crude oil (BFO M1 Europe FOB). These futures prices serve as proxies for market expectations, helping to capture anticipated cost pressures along the food value chain and thereby enhancing the forecasting performance of our models. A critical preliminary step is extending each historical commodity price series up to the start of its corresponding futures series. This alignment links the most recent historical observation to the first futures data point (e.g., for pig meat), ensuring temporal continuity and coherence across data sources, which is essential for robust forecasting.

All time series are harmonized into a common index and seasonally adjusted using the TRAMO-SEATS methodology (following both univariate and bivariate specifications, in accordance with Gómez and Maravall Herrero (1996)). We employ a bivariate adjustment for commodity prices in preparation for forecasting. In this framework, a reference series with available futures data (e.g., pig meat) informs the trend component of a related series without futures data (e.g., poultry meat). By exploiting the structural relationship between related commodity groups, this approach allows us to extrapolate the trend for series lacking futures information. Let y_t denote the observed series, x_t^{ref} the reference series, T_t the unobserved trend component, S_t denote the seasonal component and I_t the irregular component. The decomposition is given by:

$$y_t = T_t + S_t + I_t$$

where the trend is modeled as:

$$T_t = \beta x_t^{ref} + u_t, \quad \text{with } u_t \sim \text{ARIMA}(p, d, q)$$

Substituting this into the decomposition yields a RegARIMA specification:

$$y_t = \beta x_t^{ref} + \text{ARIMA}(p, d, q) + S_t + I_t$$

This structure anchors the trend to a related, economically meaningful reference series, improving the reliability of the seasonal adjustment and the underlying trend estimation.

Finally, we construct synthetic commodity price indices corresponding to the twelve food HICP subcomponents. We form these indices as unweighted averages of seasonally adjusted prices for representative products in each category (for example, butter, cheddar, skimmed milk powder, eggs, and edam cheese for dairy). This aggregation reduces idiosyncratic noise and aligns the commodity input indices with the structure of the final consumer price indices.

The final dataset, including commodity prices (extended with future prices) and producer and consumer prices, spans from January 2000 to December 2027, ensuring consistency across both historical data and forecast horizons. All food groups in these three categories are weighted by their relative importance in the HICP food basket, resulting in synthetic price indices that mirror the consumer price structure and support robust modeling and policy analysis. All time series are reported in Section A of the Appendix.

Table 1: Overview of data sources and weights by food category

Food group	HICP weight (a)	Commodity price (farm-gate)	Commodity price (futures)	Producer prices (PPI, Eurostat)	Consumer prices (HICP, Eurostat)
Bread and cereals (Cereals)	13.6	Simple average of components		Manufacture of grain mill products, starches and starch products	Bread and cereals
		BreadRye (Eurostat - DG Agri)	Bivariate adjustment		
		BreadWheat (Eurostat - DG Agri)	Milling wheat (MATIF)		
		DurumWheat (Eurostat - DG Agri)	Bivariate adjustment		
		FeedBarley (Eurostat - DG Agri)	Bivariate adjustment		
		FeedMaize (Eurostat - DG Agri)	Bivariate adjustment		
		FeedOats (Eurostat - DG Agri)	Bivariate adjustment		
		FeedRye (Eurostat - DG Agri)	Bivariate adjustment		
		FeedWheat (Eurostat - DG Agri)	Bivariate adjustment		
		MaltingBarley (Eurostat - DG Agri)	Bivariate adjustment		
Milk, cheese, and eggs (Dairy)	10.7	Simple average of components		Manufacture of dairy products	Milk, cheese and eggs
		Butter (Eurostat - DG Agri)	Bivariate adjustment		
		Cheddar (Eurostat - DG Agri)	Bivariate adjustment		
		Edam (Eurostat - DG Agri)	Bivariate adjustment		
		Eggs (Eurostat - DG Agri)	Bivariate adjustment		
		RawMilk (Eurostat - DG Agri)	Nonfat dry milk (Chicago ME)		
		Skimmed Milk Powder (Eurostat - DG Agri)	Bivariate adjustment		
Meat	16.8	Simple average of components		Processing and preserving of meat and production of meat products	Meat
		Chicken (Eurostat - DG Agri)	Bivariate adjustment		
		Cows (Eurostat - DG Agri)	Bivariate adjustment		
		PigmeatClassE (Eurostat - DG Agri)	Lean hogs (Chicago ME)		
		Steers (Eurostat - DG Agri)	Bivariate adjustment		
Fish	4.9	Not available		Processing and preserving of fish, crustaceans and molluscs	Fish
Fruits	6.8	Not available		Processing and preserving of fruit and vegetables	Fruit
Vegetables and legumes (Vegetables)	9.2	Not available		Processing and preserving of fruit and vegetables	Vegetables
Oils and fats	2.4	Simple average of components		Manufacture of vegetable and animal oils and fats	Oils and fats
		OliveOil (Eurostat - DG Agri)	Bivariate adjustment		

Table 1 continued

Food group	HICP weight (a)	Commodity price (farm-gate)	Commodity price (futures)	Producer prices (PPI, Eurostat)	Consumer prices (HICP, Eurostat)
		Rapeseed ((International Monetary Fund Primary Commodity Price System))	Rapeseed futures (MATIF)		
		Soya (International Monetary Fund Primary Commodity Price System)	Bivariate adjustment		
		Sunflower (Hamburg WeltWirtschaftsInstitut, HWWI)	Bivariate adjustment		
Sugar, jam, honey, chocolate, and confectionery (Sugar)	4.8	EU data, completed with International data when EU data are not available		Manufacture of sugar	Sugar, jam, honey, chocolate and confectionery
		Whitesugar (EU) (Eurostat - DG Agri)	White sugar futures (LIFFE)		
		Whitesugar (International Sugar Organization)			
Coffee, tea, and cocoa (Coffee)	2.5	Coffee price (International Coffee Organization)	Arabica coffee (Brazil's BMF)	Processing of tea and coffee	Coffee, tea and cocoa
Food products not elsewhere classified (Food n.e.c.)	3.5	Not available		Manufacture of other food products	Food products n.e.c.
Mineral waters, soft drinks, and juices (Non alcoholic beverages)	4.8	Not available		Simple average of Manufacture of soft drinks; production of mineral waters and other bottled waters and Manufacture of fruit and vegetable juice	Mineral waters, soft drinks, fruit and vegetable juices
Alcohol and tobacco	20.0	Tobacco (World Bank - Pink Sheet)		Simple average of Manufacture of beverages and Manufacture of tobacco products	Alcoholic beverages, tobacco

Note: For categories lacking a specific commodity index (fruits, vegetables, fish, food n.e.c., non-alcoholic beverages), the overall commodity index is used as a proxy. Monthly data span 2000 to 2025m5 (PPI) and 2025m6 (commodities & HICP). a) HICP weights are euro area averages for 2020–2025.

3 Models and Applications

3.1 Food Value Chain Model

This section presents a short-term forecasting framework aimed at quantifying the pass-through of shocks from food and energy (fuel) commodity prices to consumer food inflation in the euro area. It hinges upon Borrallo, Cuadro-Sáez, Gras-Miralles, and Pérez (2024) and applies its methodology to the complete database described in Section 2 to mimic the HICP composition. The approach builds upon the well-established Food Value Chain Model of Ferrucci, Jiménez-Rodríguez, and Onorante (2012), incorporating energy (fuel) prices as an additional external driver and accounting for non-linearities, as in Kilian and Vigfusson (2011). The modeling strategy centers on a vector autoregressive model with exogenous variables (VARx) applied to seasonally adjusted food price series in monthly log-differences, as represented by the following equation:

$$y_t = c + \sum_{i=0}^{I} A_i y_{t-i} + \sum_{i=0}^{J} \beta_i p_{t-i} + \sum_{i=0}^{K} B_i x^*_{t-i} + \sum_{i=0}^{L} C_i p^*_{t-i} + \epsilon_t \tag{1}$$

where y_t represents the vector of commodity, producer, and consumer food prices. Each price equation includes lags of all three price series ($\sum_{i=0}^{I} A_i y_{t-i}$) and current and lagged fuel prices p_t ($\sum_{i=0}^{J} \beta_i p_{t-i}$). The term x^*_t is a non-linear transformation of the commodity price index (the first element of y_t), and p^*_t is a non-linear transformation of the fuel price p_t. Both non-linear variables are defined following Hamilton (1996). Specifically, let yc_t be the first element of y_t. Then:

$$x^*_t = max(0, yc_t - max(yc_{t-1}, yc_{t-2}, ..., yc_{t-12})) \tag{2}$$

$$p^*_t = max(0, p_t - max(p_{t-1}, p_{t-2}, ..., p_{t-12})) \tag{3}$$

Equations (2) and (3) compare each month's price with the maximum value observed over the preceding 12 months. This captures price increases that exceed the corrections of previous declines, addressing the stylized fact that many observed price increases are simply corrections of earlier decreases.

Notice that the model can be estimated as a linear specification by omitting the terms that capture asymmetries, namely $\sum_{i=0}^{K} B_i x^*_{t-i} + \sum_{i=0}^{L} C_i p^*_{t-i}$. In this case, estimation proceeds via a VARx approach. Alternatively, the model can be estimated in its non-linear form, as presented in equation 1. To avoid the bias that a VARx estimation may induce when applied to the non-linear specification, the estimation procedure follows Kilian and Vigfusson (2011) (see Borrallo, Cuadro-Sáez, Gras-Miralles, and Pérez (2024) for further details).

Also, this model could be in principle estimated by means of a bottom-up approach or a top-down approach, which are explained in detail below.

- **Top-down approach**: The top down approach consists in estimating a single-equation model using aggregate-level indicators that capture the overall dynamics of the food sector. Specifically, the model is specified using the total food commodity price index, the industrial production index for the food sector, and the aggregate consumer price index for food. This method abstracts from individual food categories. In some cases, estimating the model directly on the aggregate food index may be necessary or advisable. This applies not only when disaggregated data by food components are unavailable, but also when benchmarking against studies that have used an aggregate food price index as the basis for their analysis (see Section 3.2 for an illustration).

- **Bottom-up approach**: This approach involves modeling individual food categories separately and aggregating their estimated impulse responses, rather than relying on aggregate indices of commodity, producer, and consumer prices to estimate a single VARx model (the top-down approach). As highlighted by Ferrucci, Jiménez-Rodríguez, and Onorante (2012), the two approaches may yield different results, since aggregate indices can obscure the item-specific dynamics of price pass-through and may only provide approximate estimates—particularly in the presence of non-linearities or strong cross-effects among different goods. The bottom-up approach, by contrast, allows for a more granular and accurate representation of heterogeneous transmission mechanisms across food groups, which is essential for understanding the differentiated impact of commodity price fluctuations.

In this application, unless specified, we follow the bottom-up approach, following Ferrucci, Jiménez-Rodríguez, and Onorante (2012). We first estimate model (1) separately for each of the twelve main food categories in the euro area HICP (cereals, dairy, meat, fish, vegetables, fruits, oils and fats, sugar, coffee, food n.e.c., non-alcoholic beverages, and alcohol and tobacco; corresponding to ECOICOP groups 01 and 02). We then construct a reference food index by weighting each category's impulse response function by its weight in the HICP.

As for the estimation, we assume a Cholesky identification scheme.

3.1.1 Results of the Linear Model

Estimating the linear specification of the model reduces to estimating Equation (1) discarding the non-linear terms, i.e. with the terms $\sum_{i=0}^{K} B_i x_{t-i}^* + \sum_{i=0}^{L} C_i p_{t-i}^*$ inactive.

Results are presented in Figure 2. The impulse response functions show a significant, persistent impact of both commodity and fuel shocks on euro area food inflation, with the effect peaking after 12 to 15 months: a 10% shock to food commodity prices raises food inflation by about 3 percentage points, and a 10% fuel price shock raises it by about 0.35 percentage points at the peak.[1] Among the food categories, dairy, meat, cereals, and vegetables contribute the most to the HICP food inflation response.

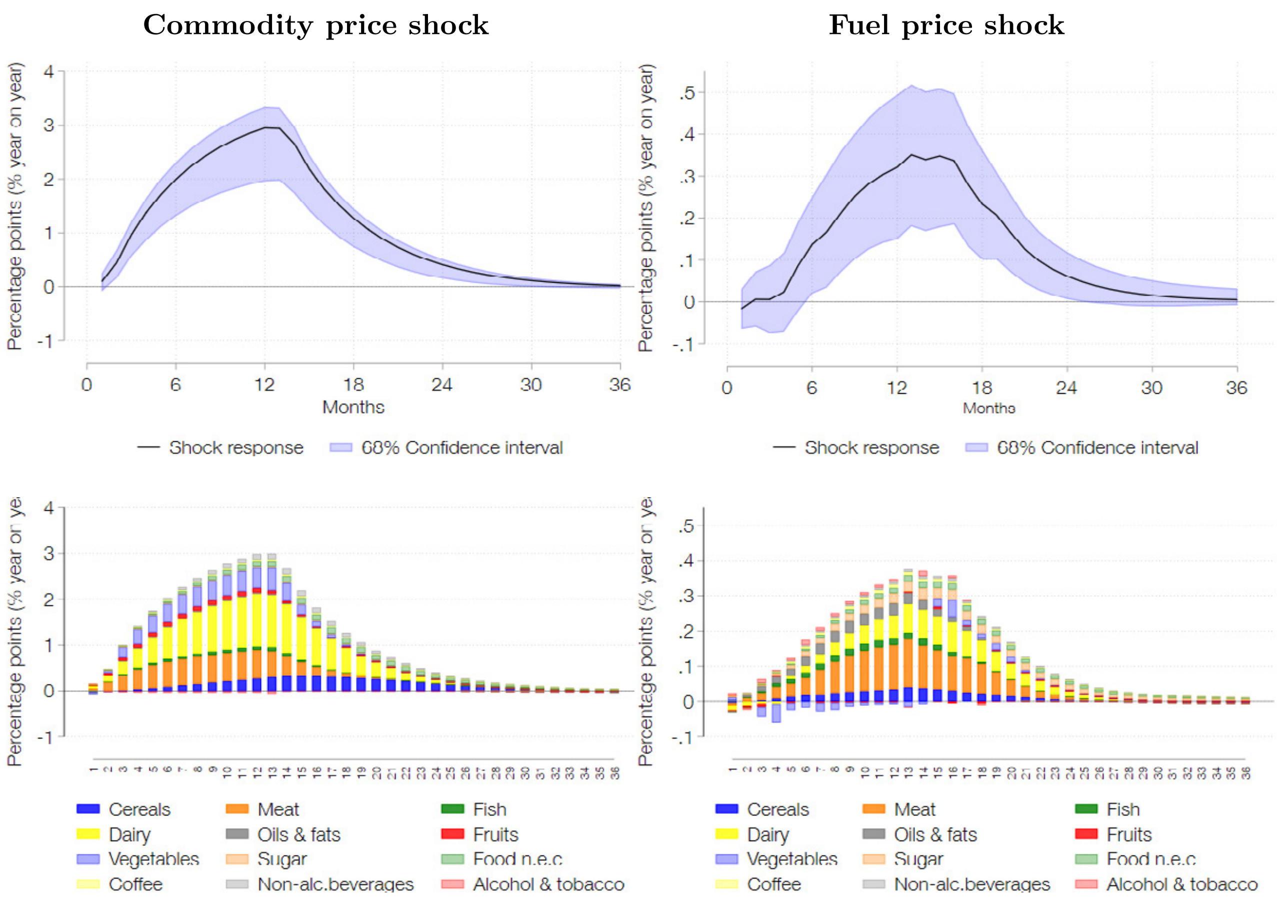
In addition, Figure 3 presents a historical decomposition of euro area food inflation based on the linear version of model (1), illustrating how each stage of the value chain contributed to deviations of food inflation from its long-term trend over time on the first panel (Figure 3a). During the high-inflation period from 2022 to 2024, energy, food commodities, industrial food production, and the final retail stage all made substantially larger contributions to these deviations than in earlier periods. The synchronized upward influence of all factors is characteristic of that period, at least within the sample shown in the figure (2020-2025). In turn, in Figure 3b we show the decomposition by food groups.

3.1.2 Results of the Non-Linear Model

Estimating the non-linear version of the model means estimating equation (1) including the non-linear terms. Results are presented in Figure 4 and show that the effects are asymmetric: upward price shocks in food and energy commodities have a significant positive effect on food consumer prices, while downward price shocks have a milder effect for food commodities and

[1] The results for each food category are available in the Appendix, Tables B.1, B.2 and B.3.

Figure 2: Food inflation response to food commodity and to fuel price shocks
Linear model



Note: this figure shows the year-on-year food inflation response to a 10% increase in food commodity prices (left panel) and to a 10% increase in fuel prices (right panel), assuming the linear version of the model specified in Equation 1; thus, this linear version of the model assumes that the terms $\sum_{i=0}^{K} B_i x^*_{t-i} + \sum_{i=0}^{L} C_i p^*_{t-i}$ in the model are zero. The upper panel shows the 68% bootstrap confidence intervals for the response; the lower panel shows the contribution of each food group to the reaction function.

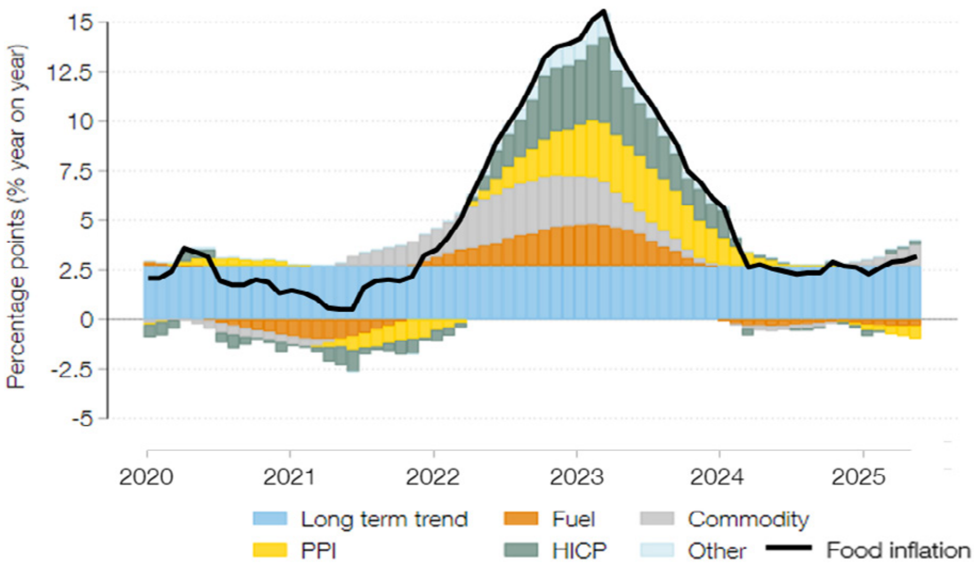
no statistically significant effect for energy commodities. Namely, a 10 percent positive shock in food commodity prices induces a food consumer price increase of 3 percent, whereas a negative shock translates into a reduction of 2.1 percent in food consumer prices. The same shocks on fuel prices cause a positive impact on food consumer prices of 0.4 percent (positive shock) and, notably, a 10 percent decrease in fuel prices does not have a significant impact on food consumer prices (see Figure 4).[2]

Both the linear and non-linear versions of the VARx model provide quantitative estim-

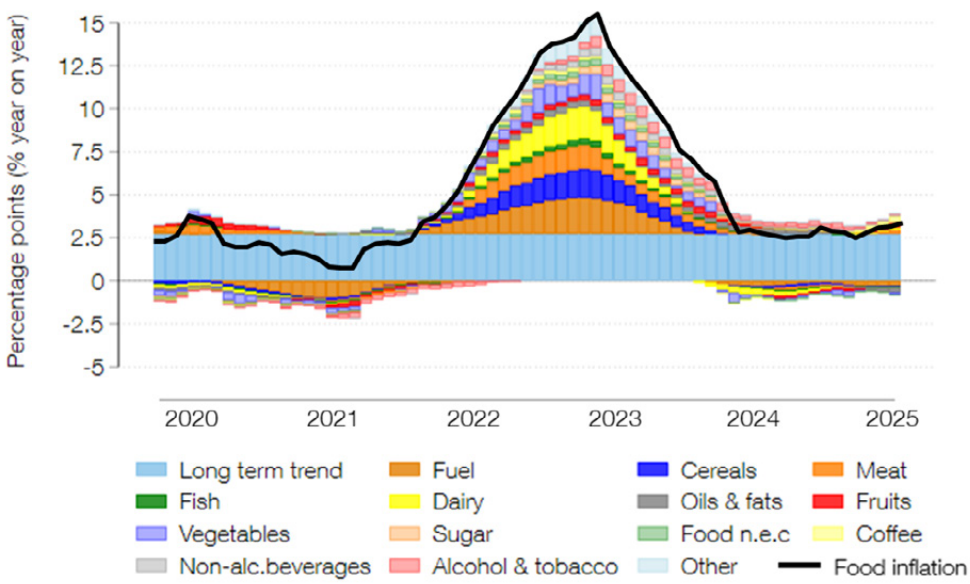
[2]The results for the non-linear model are available from the authors upon request.

Figure 3: Drivers of euro area food inflation. Value chain vs. food group contributions

(a) Contributions of each value chain stage

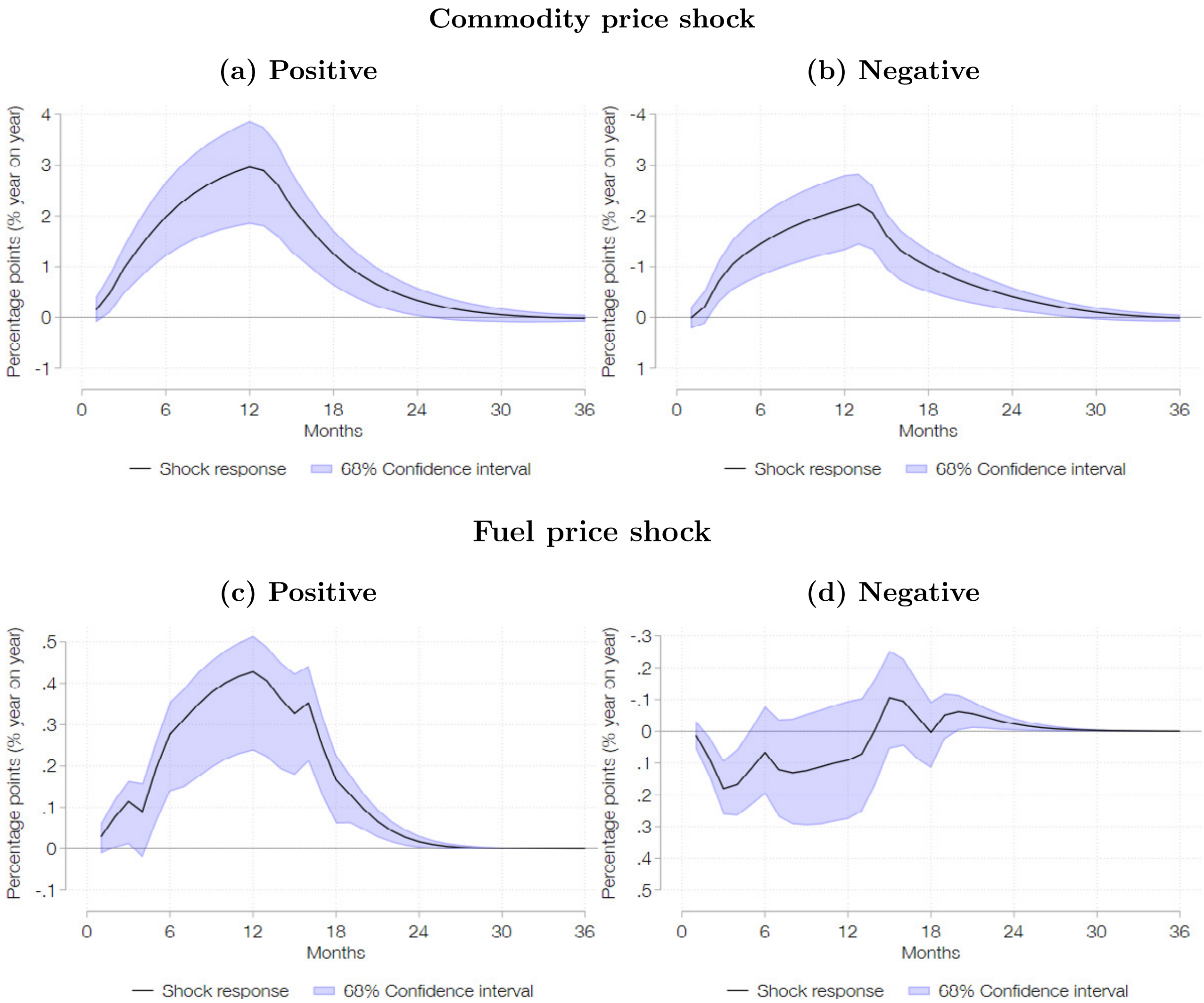


(b) Contributions of each food group



Note: the first panel of the figure illustrates the contribution of each stage in the value chain (farm, industry, retail) to the deviation of food inflation from its long-term trend. "Other" captures a minor residual discrepancy arising from the specific time series treatment applied in the model. The second panel shows the contribution of each food group to the deviation of food inflation from its long-term trend adding up deviations from commodity prices, producer prices, and consumer prices per food group.

Figure 4: Food inflation response to positive vs. negative shocks
Non-linear model

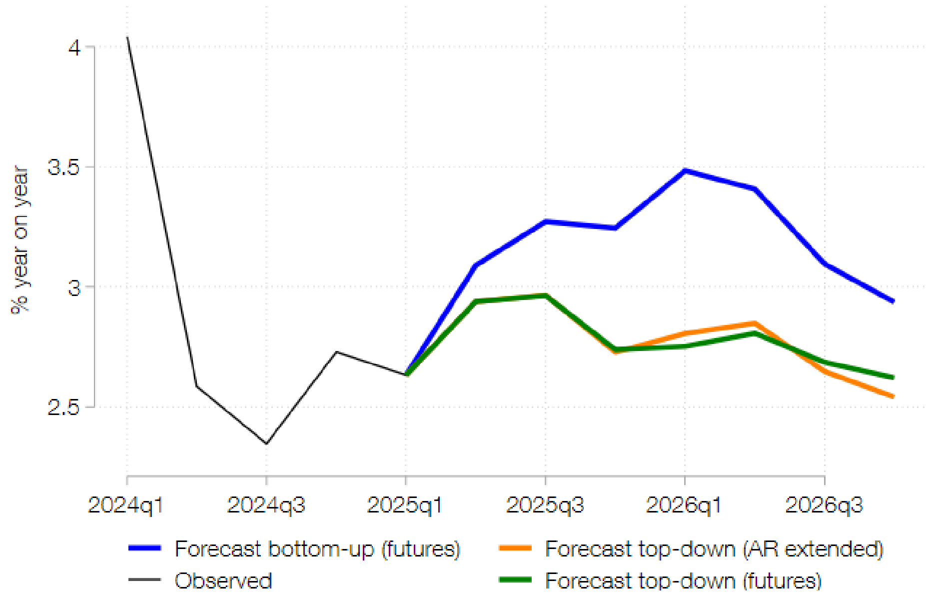


Note: the figure illustrates food inflation's response to a 10% increase (left panels) in food commodity and fuel prices vs. a 10% decrease (right panels) according to the model specified in Equation 1. Includes non linear terms to capture asymmetry. Dotted lines represent 68% bootstrap confidence intervals. For ease of comparison, y-axes in negative shock panels are inverted.

ates of the impact of food and energy commodity shocks on consumer food prices. These results are very similar to the ones presented in Borrallo, Cuadro-Sáez, Gras-Miralles, and Pérez (2024), with the main novelty that in this report they are capturing the entire HICP basket. Moreover, these models enable the calculation of short-term forecasts in two forms: as unconditional forecasts (letting the model run without external inputs) and as conditional forecasts (incorporating additional information, such as financial market data), as we explain in the following section.

3.2 Conditional Forecasts

Figure 5: Quarterly food inflation forecasts under alternative modeling approaches



Note: This figure presents quarterly food inflation forecasts generated under three modeling strategies: (i) a bottom-up approach assuming commodity prices follow futures as of June 18^{th}, 2025; (ii) a top-down approach with the same futures-based assumption; and (iii) a top-down approach where commodity prices evolve according to an autoregressive process. All forecasts are based on the linear specification of equation 1.

One important application of these models is in generating forecasts. Using the linear specification of the VARx model in Equation 1, we employ food commodity futures prices as forward-looking paths for commodity price evolution, constructing dynamic projections for both producer (industrial) and consumer food prices. We provide in Figure 5 an example of such approach using data available as of 18 June 2025. The prescription of the model conditional on such information set would indicate that food inflation would rise above its historical average during 2025, primarily driven by pronounced increases in dairy and meat prices, and moderate in 2026, although remaining above its historical average.

The figure also presents the model's top-down approach, in which Equation 1 is estimated for the aggregate food price index. The forecast is lower than that obtained through the bottom-up approach, as price variations in certain components tend to offset increases in others, thereby masking the overall impact of commodity price movements. Two versions of the top-down forecast are shown: one conditioned on futures prices, and another based on an unconditional projection of the aggregate commodity price index, obtained from an ARIMA model.

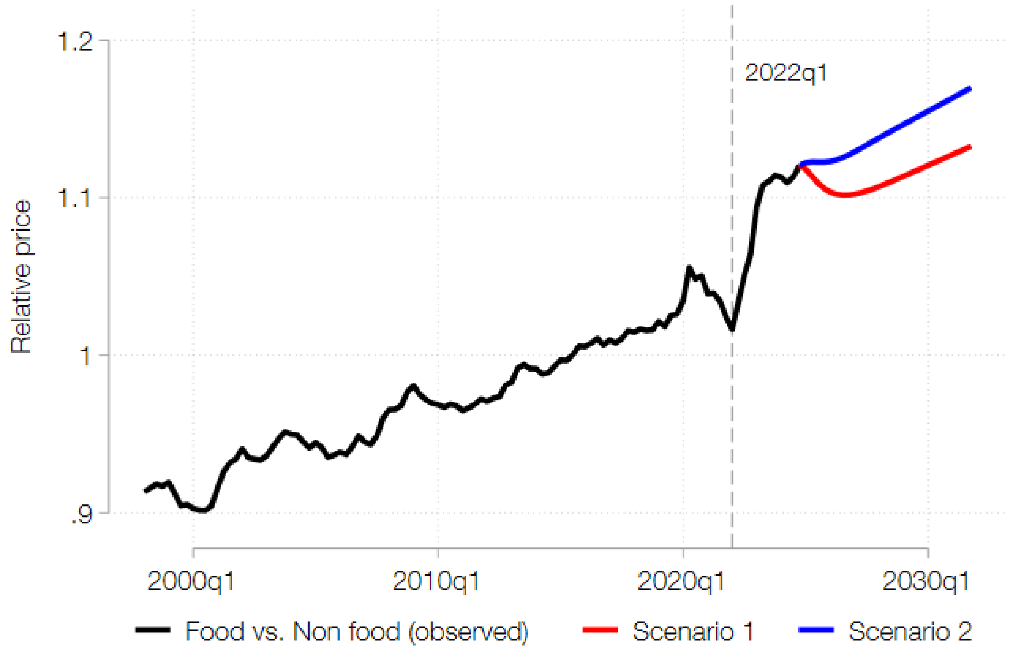
Beyond relying solely on futures-based conditioning, central banks can further enhance their forecasting frameworks by exploring a broader set of conditional approaches. Scenario-based assumptions (such as supply shocks, policy changes, or demand surges) allow for stress testing under plausible economic scenarios. Model-consistent paths derived from structural models (e.g., DSGEs or BVARs) ensure internal coherence across macroeconomic variables. Market-implied expectations from options or commodity-linked instruments enrich the probabilistic dimension of forecasts. Emerging machine learning techniques offer innovative ways to simulate counterfactual scenarios or identify key drivers of inflation dynamics. Together, these approaches provide a more flexible and robust toolkit for anticipating food price developments under varying economic conditions.

3.3 Long-Term Forecasting: Vector Error Correction Model

This section relies on the quarterly Vector Error Correction Model (VECM) by Bonino-Gayoso, Cuadro-Sáez, and Ghirelli (2025) to project the medium-term evolution of the relative price of food to non-food items. This approach is particularly useful when food prices diverge from the rest of the consumption basket, as it provides a formal framework to assess whether such deviations are statistically significant, whether they reflect profound changes that warrant closer monitoring, and whether a reversion to previous relative price levels can be expected. We use the non-food price index as the basis of the relative price (instead of the overall consumer price index) to avoid the artificial correlation that would arise from including food in both the numerator and denominator, thereby clarifying the cointegration relationship. The relative prices time series is plotted in Figure 6, and displays an upward trend over time, with a sharp increase in 2022Q2, suggesting a level shift.

The VECM formulation allows for the joint modeling of the long-run relationship and the short-term dynamics of adjustment toward the long-run equilibrium between food and

Figure 6: Relative food vs. nonfood price index (euro area) - Two scenarios



Note: the figure presents the ratio of food to non-food prices, with projections under: Scenario 1 (no structural break, model est. through 2022Q1) and Scenario 2 (with a 2022Q2 level shift). In Scenario 1 (red), relative prices eventually return to the old trend; in Scenario 2 (blue), the post-2022 jump is permanent. Dashed line marks the start of 2022Q2 break.

non-food prices, as captured by the following equations:

$$\begin{aligned}\Delta Y_t &= \alpha_{1,0} + \alpha_{1,1}\left(Y_{t-1} - \beta_0 - \beta_1 X_{t-1}\right) + \sum_{j=1}^{p-1} \gamma_{1,j} \Delta Y_{t-j} + \sum_{j=1}^{p-1} \delta_{1,j} \Delta X_{t-j} + \epsilon_{1,t} \\ \Delta X_t &= \alpha_{2,0} + \alpha_{2,1}\left(Y_{t-1} - \beta_0 - \beta_1 X_{t-1}\right) + \sum_{j=1}^{p-1} \gamma_{2,j} \Delta Y_{t-j} + \sum_{j=1}^{p-1} \delta_{2,j} \Delta X_{t-j} + \epsilon_{2,t}\end{aligned} \quad (4)$$

where Y_t and X_t denote the logarithms of the food and non-food price indices, respectively, and p is the number of lags included. The optimal number of lags is determined using standard selection criteria (AIC, SBIC, HQIC). The term in parentheses, $Y_{t-1} - \beta_0 - \beta_1 X_{t-1}$, represents the deviation from the long-run equilibrium. Each equation captures the short-run dynamics of food and non-food prices, including the adjustment mechanism.

The results indicate that a long-run relationship exists, but a structural break is detected in 2022Q2 (as confirmed by the Zivot–Andrews test). Therefore, we consider two forecast scenarios. In the first scenario, we assume the relationship is governed by parameters estimated up to 2022Q1, which leads the model to forecast a quick return to the pre-2022 long-run equilibrium path. In the second scenario, we incorporate data through 2024Q4 and explicitly account for the 2022Q2 break (see Table B.4). This scenario presents a markedly different picture: food prices do not revert to the old equilibrium path but instead follow a persistently higher trajectory. In other words, food prices remain relatively more expensive in the medium term compared to other items in the consumption basket.

4 Final Considerations

In addition to the points covered in previous sections, three important food security factors influencing food commodity prices remain unaddressed. First, geopolitical relations with major extra-EU trading partners can change abruptly, as seen in recent episodes. Second, independent of global commodity trends, domestic imbalances in critical inputs (e.g., fertilizers) can sharply affect food security and drive up prices along the food value chain. Lastly, climate change is a major risk to food production. In this respect, Naumann, Cammalleri, Mentaschi, and Feyen (2021) estimate that without climate change mitigation, the largest agricultural losses would occur in the Mediterranean and Atlantic agricultural sectors. In the same vein, Banco de España (2022) warns of heightened wildfire and desertification risks in southern European countries due to climate change. More recently, Pieralli and Pérez-Domínguez (2025) show that extreme weather events in the EU may negatively affect food supply and trade, undermining the resilience of EU agricultural markets. Beyond these factors, cyclical climate patterns such as El Niño can influence euro area food prices even when production disruptions occur in distant regions (Borrallo, Cuadro-Sáez, Ghirelli and Pérez (2024)).

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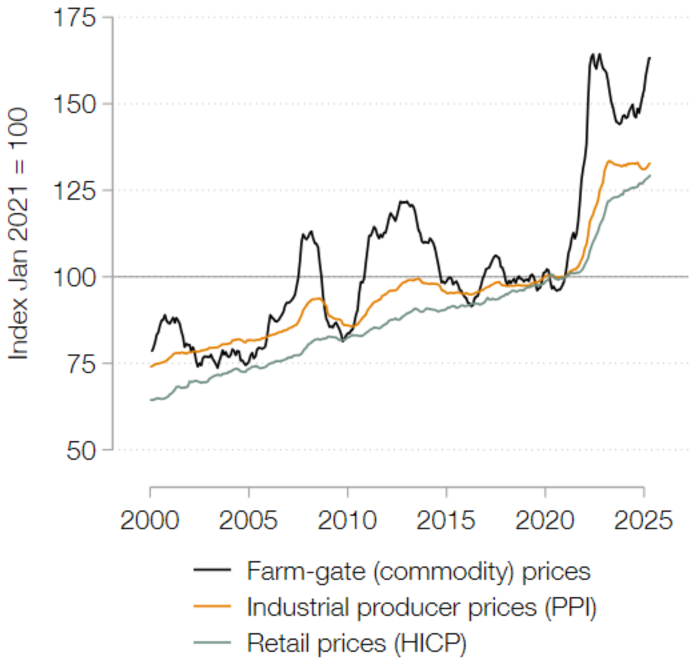
Appendix

A Graphical Representation of the Database

Figure A.1: Aggregate food commodity, producer, and consumer price indices

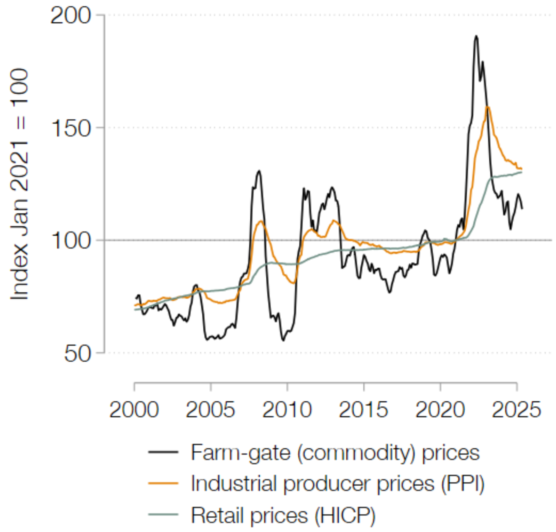


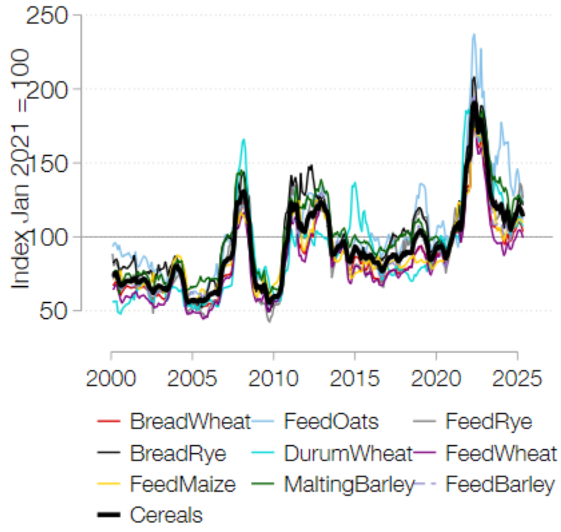
Note: The figure illustrates food price indices at three stages of the value chain: European Union commodity prices, also known as farm prices, euro area producer prices (PPI), and euro area consumer prices (HICP), all indexed to January 2021 = 100.

Figure A.2: Food price indices by food group
Prices along the value chain and commodity breakdown

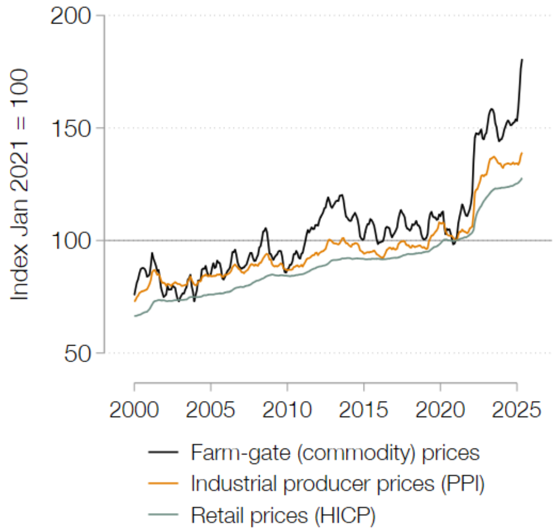
Commodity, producer and consumer prices | **Commodity breakdown**

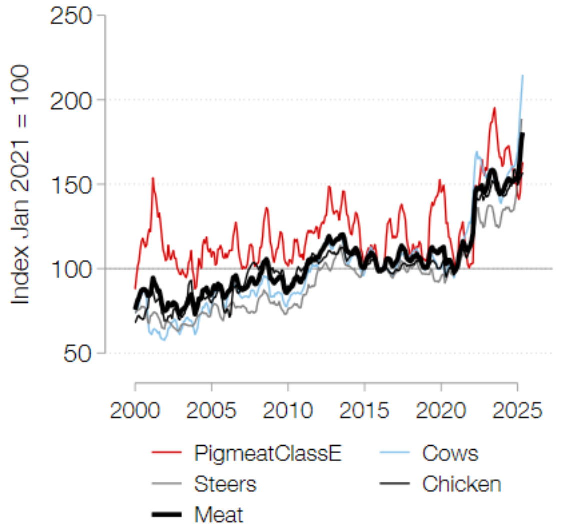
(a) Cereals





(b) Meat



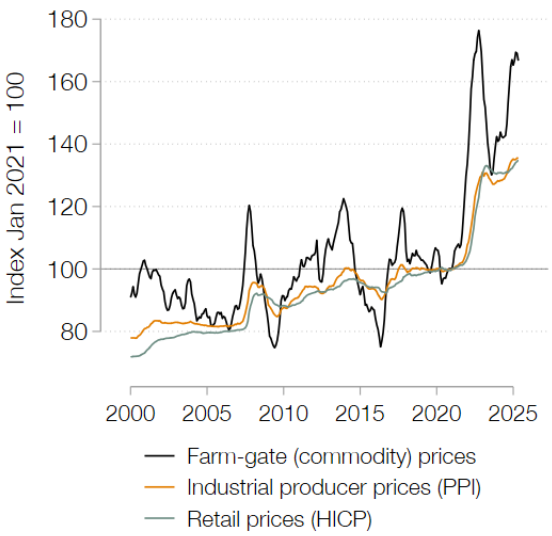


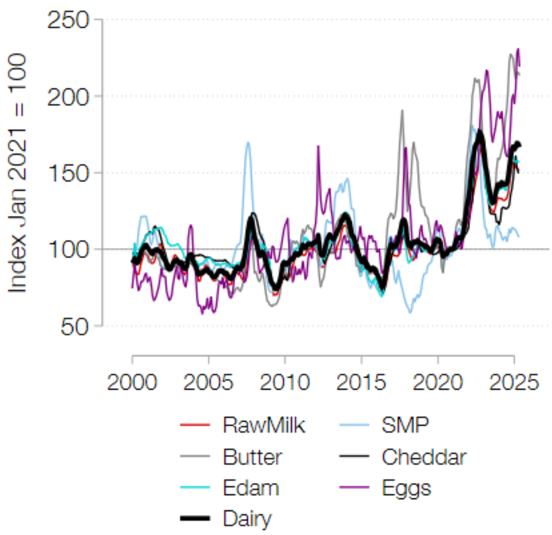
Note: Left panels show price trends across the food supply chain in the euro area: farm-gate prices from the European Union (what farmers receive) from the European Commission's agriculture data portal[3], euro area producer prices (what manufacturers charge) from Eurostat's industrial production data[4], and euro area consumer prices (what shoppers pay) from Eurostat's inflation index for food[5]. The right panel breaks down farm-gate prices by food category, using data from the same source. Group averages are calculated as simple averages of the individual items in each category.

Figure A.2: Food price indices by food group
Prices along the value chain and commodity breakdown (continued)

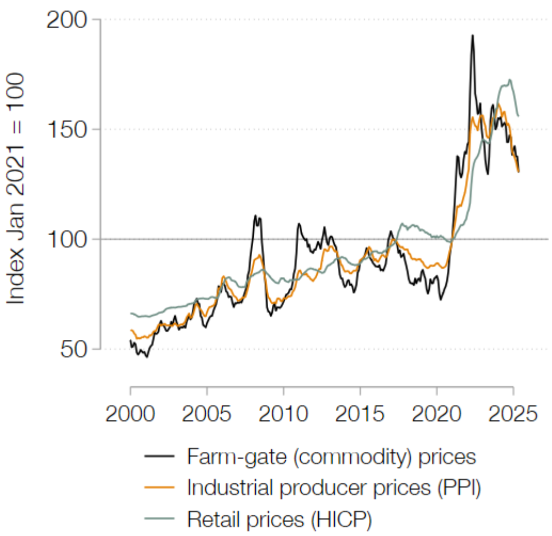
Value chain **Commodity composition**

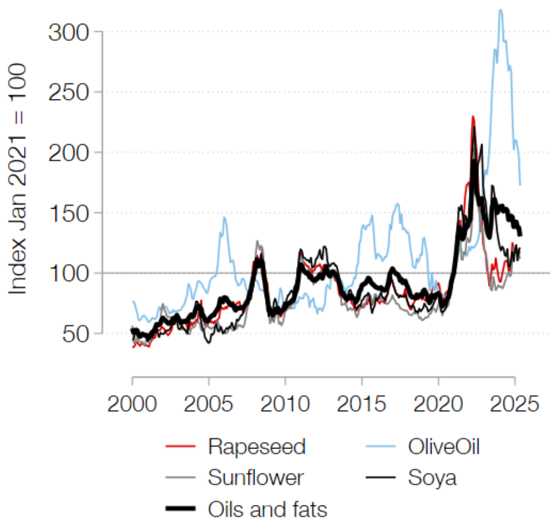
(c) Dairy





(d) Oils and fats

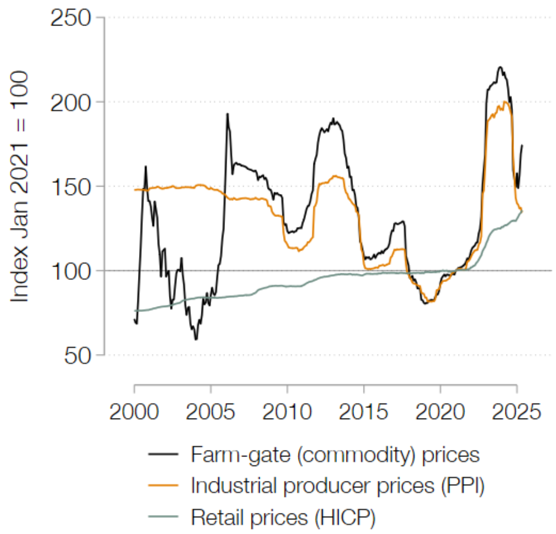




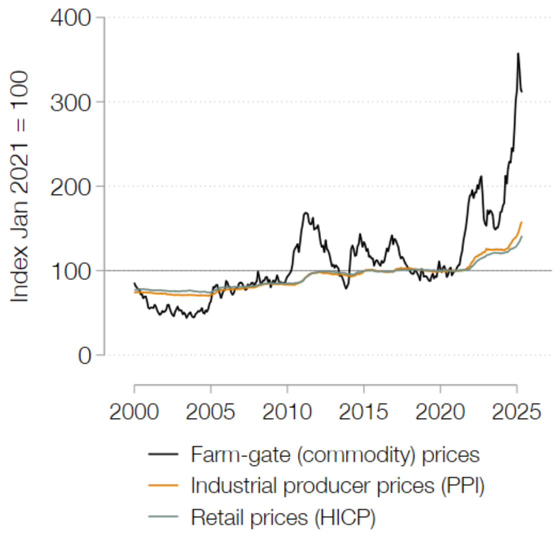
Note: Left panels show price trends across the food supply chain in the euro area: farm-gate prices from the European Union (what farmers receive) from the European Commission's agriculture data portal[6], euro area producer prices (what manufacturers charge) from Eurostat's industrial production data[7], and euro area consumer prices (what shoppers pay) from Eurostat's inflation index for food[8]. The right panel breaks down farm-gate prices by food category, using data from the same source. Group averages are calculated as simple averages of the individual items in each category.

Figure A.2: Food price indices by food group
Prices along the value chain (continued)

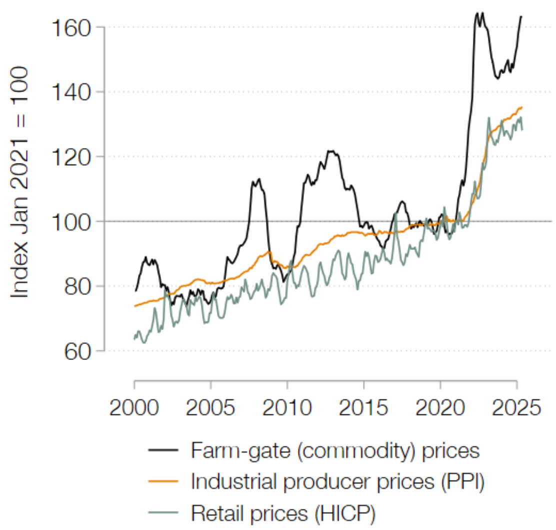
(e) Sugar



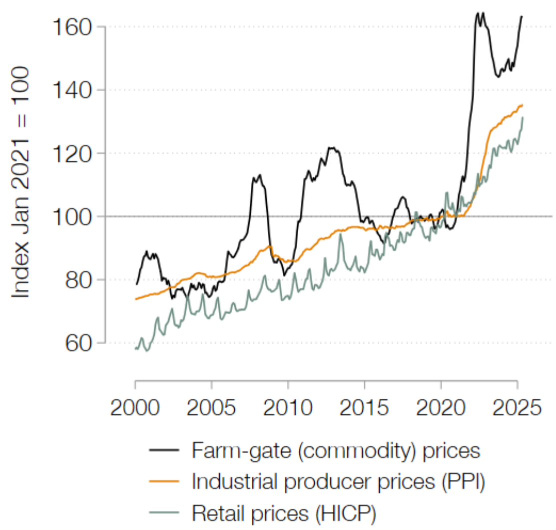
(f) Coffee



(g) Vegetables



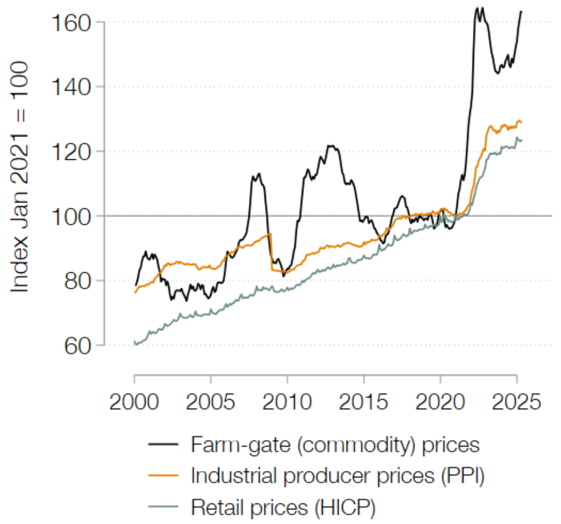
(h) Fruits



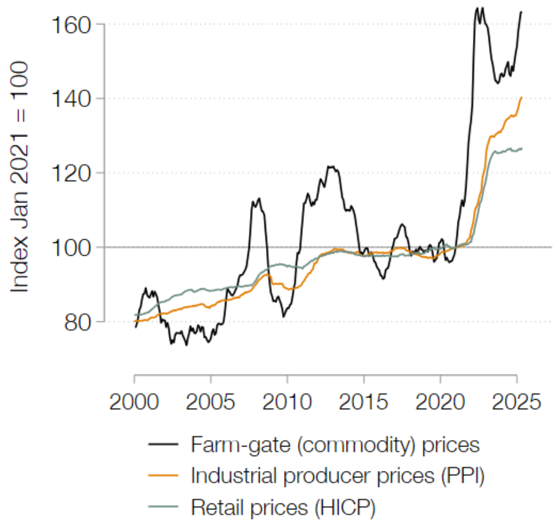
Note: Left panels show price trends across the food supply chain in the euro area: farm-gate prices from the European Union (what farmers receive) from the European Commission's agriculture data portal[9], euro area producer prices (what manufacturers charge) from Eurostat's industrial production data[10], and euro area consumer prices (what shoppers pay) from Eurostat's inflation index for food[11]. For categories lacking a specific commodity index (fruits, vegetables, fish, food n.e.c., non-alcoholic beverages), the overall commodity index is used as a proxy.

Figure A.2: Food price indices by food group
Prices along the value chain (continued)

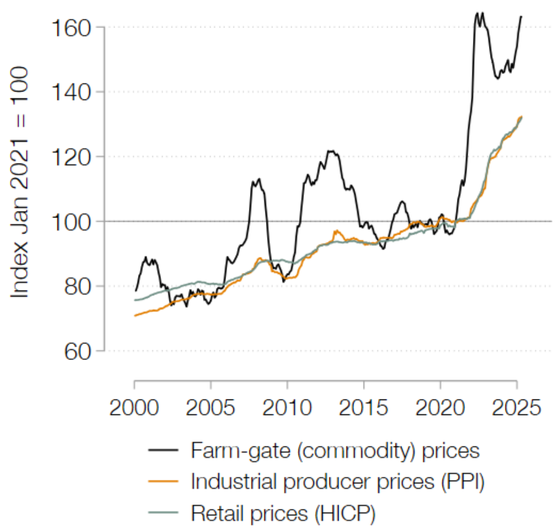
(i) Fish



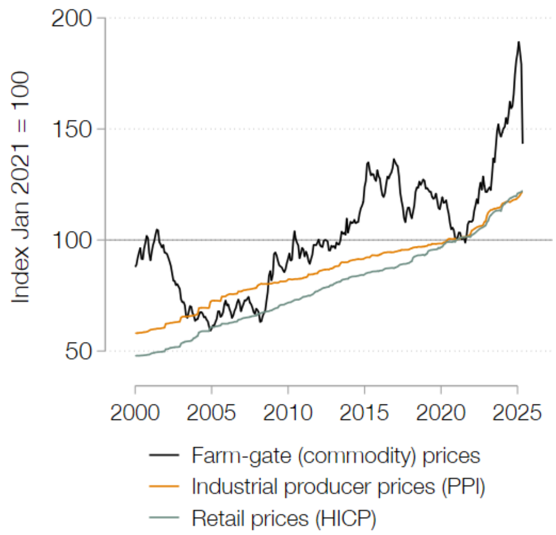
(j) Food, n.e.c.



(k) Non-alcoholic beverages



(l) Alcohol and tobacco



Note: Left panels show price trends across the food supply chain in the euro area: farm-gate prices from the European Union (what farmers receive) from the European Commission's agriculture data portal[12], euro area producer prices (what manufacturers charge) from Eurostat's industrial production data[13], and euro area consumer prices (what shoppers pay) from Eurostat's inflation index for food[14]. For categories lacking a specific commodity index (fruits, vegetables, fish, food n.e.c., non-alcoholic beverages), the overall commodity index is used as a proxy.

B Estimation Results

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Table B.1: Linear model estimated parameters by food group: cereals, dairy, meat and fish

	Cereals			Dairy			Meat			Fish		
	C	P	H	C	P	H	C	P	H	C	P	H
Comm lag (-1)	0.730***	0.076***	0.001**	0.403***	0.090**	0.006**	0.355***	0.218***	0.005**	0.669***	-0.008	0.001
	(11.99)	(5.35)	(2.51)	(6.47)	(2.90)	(2.61)	(3.60)	(4.37)	(2.52)	(10.98)	(-0.21)	(1.07)
Comm lag (-2)	-0.190**	0.100***	0.000	0.042	0.074**	0.003				-0.070	0.070*	0.001
	(-2.44)	(5.51)	(0.39)	(0.66)	(2.35)	(1.19)				(-1.13)	(1.77)	(0.75)
Comm lag (-3)	0.011	0.031	-0.001									
	(0.14)	(1.60)	(-1.35)									
Comm lag (-4)	0.145*	-0.017	-0.001									
	(1.91)	(-0.98)	(-1.58)									
PPI lag (-1)	-0.004	0.165**	0.010***	0.409***	0.497***	0.016***	-0.135	0.106	0.011**	-0.033	-0.042	0.003**
	(-0.01)	(2.59)	(5.75)	(3.17)	(7.72)	(3.11)	(-0.65)	(1.01)	(2.38)	(-0.36)	(-0.70)	(2.55)
PPI lag (-2)	0.073	0.095	-0.001	0.222	0.173**	0.007				-0.073	0.039	0.006***
	(0.26)	(1.47)	(-0.69)	(1.64)	(2.57)	(1.28)				(-0.78)	(0.65)	(4.85)
PPI lag (-3)	-0.134	0.282***	0.006***									
	(-0.52)	(4.66)	(3.45)									
PPI lag (-4)	0.169	-0.001	-0.006***									
	(0.70)	(-0.03)	(-3.51)									
HICP lag (-1)	1.020	3.192	0.613***	-3.938**	-1.107	0.405***	-0.228	1.877*	0.640***	-5.816	2.774	-0.011
	(0.11)	(1.49)	(9.95)	(-2.43)	(-1.37)	(6.47)	(-0.11)	(1.81)	(14.50)	(-1.37)	(1.02)	(-0.19)
HICP lag (-2)	-6.475	-1.398	0.021	-0.962	0.571	0.188***				4.014	6.255**	0.018
	(-0.60)	(-0.56)	(0.29)	(-0.64)	(0.76)	(3.23)				(0.95)	(2.32)	(0.32)
HICP lag (-3)	-14.556	1.326	-0.017									
	(-1.38)	(0.54)	(-0.24)									
HICP lag (-4)	7.535	-1.644	0.203***									
	(0.91)	(-0.85)	(3.64)									
Constant	0.391*	0.021	0.003**	0.100*	0.033	0.003	0.110	0.037	0.009***	0.094	0.026	0.009***
	(1.88)	(0.43)	(2.03)	(1.92)	(1.26)	(1.55)	(1.12)	(0.76)	(4.31)	(0.92)	(0.40)	(6.67)
Fuel	-0.023	-0.002	-0.000**	0.032***	-0.001	-0.001***	0.059***	0.007	-0.001**	0.022	-0.006	0.000
	(-0.65)	(-0.23)	(-2.01)	(3.04)	(-0.24)	(-3.13)	(3.44)	(0.78)	(-2.06)	(1.27)	(-0.55)	(0.78)
Fuel(-1)	0.037	0.004	0.001***	0.009	0.007	0.000	0.024	0.025**	0.002***	0.017	0.032**	0.000
	(1.00)	(0.46)	(2.89)	(0.85)	(1.33)	(1.15)	(1.37)	(2.75)	(4.55)	(0.93)	(2.78)	(0.01)
Fuel(-2)	-0.011	-0.008	0.000	-0.000	0.002	0.000	0.023	0.003	-0.001*	-0.006	0.020*	0.000
	(-0.30)	(-0.94)	(0.51)	(-0.02)	(0.39)	(0.25)	(1.28)	(0.37)	(-1.81)	(-0.34)	(1.76)	(1.00)
Fuel(-3)	-0.015	0.002	0.000	-0.010	0.001	-0.001	0.007	0.003	0.000	0.002	0.004	0.000
	(-0.40)	(0.24)	(1.26)	(-0.94)	(0.23)	(-1.53)	(0.38)	(0.31)	(0.26)	(0.14)	(0.33)	(0.49)
Fuel(-4)	0.024	0.001	0.000	0.010	0.001	0.001***	0.003	-0.005	-0.001	0.016	0.014	0.000
	(0.66)	(0.15)	(1.18)	(0.97)	(0.10)	(2.60)	(0.19)	(-0.53)	(-1.52)	(0.91)	(1.24)	(0.71)
Fuel(-5)	-0.050	0.001	0.000	0.017	0.006	0.000	0.028	0.010	0.001**	-0.006	0.013	0.000
	(-1.42)	(0.18)	(0.37)	(1.58)	(1.20)	(0.37)	(1.62)	(1.11)	(2.57)	(-0.33)	(1.15)	(0.46)
Fuel(-6)	0.079**	0.011	0.000	0.003	-0.005	-0.000	0.037**	0.025**	0.001**	0.032*	-0.005	0.000
	(2.30)	(1.35)	(0.29)	(0.28)	(-0.94)	(-1.16)	(2.14)	(2.88)	(2.03)	(1.84)	(-0.43)	(0.18)
Summary Statistics												
R-squared	0.490	0.754	0.855	0.472	0.650	0.724	0.237	0.407	0.744	0.442	0.149	0.188
Adj. R-squared	0.454	0.736	0.845	0.447	0.634	0.711	0.210	0.386	0.735	0.416	0.109	0.150
S.E. equation	2.750	0.643	0.018	0.823	0.410	0.032	1.372	0.692	0.029	1.377	0.883	0.019
F-statistic	13.799	43.947	84.968	19.185	39.835	56.280	8.750	19.389	81.981	16.994	3.755	4.971
Log likelihood	-701.8	-276.1	764.5	-351.5	-147.3	601.8	-502.9	-302.4	622.6	-502.4	-372.1	753.0
Akaike AIC	4.927	2.021	-5.082	2.495	1.101	-4.012	3.508	2.139	-4.175	3.525	2.636	-5.044
Schwarz SC	5.178	2.272	-4.831	2.671	1.277	-3.836	3.646	2.277	-4.036	3.701	2.811	-4.868
Mean dependent	0.185	0.214	0.029	0.225	0.183	0.022	0.206	0.191	0.035	0.204	0.166	0.012
S.D. dependent	3.723	1.253	0.047	1.107	0.677	0.059	1.544	0.884	0.057	1.802	0.936	0.021

Note: Columns are grouped by food (cereals, dairy, meat and fish), with three subcolumns for commodity (C), producer price index (P), and consumer price index (H). Coefficients are in the first line (with stars denoting significance levels: * 10%, ** 5%, *** 1%). T-statistic in the second line.

Table B.2: Linear model estimated parameters by food group: vegetables, fruits, oils & fats and sugar

	Vegetables			Fruits			Oils & Fats			Sugar		
	C	P	H	C	P	H	C	P	H	C	P	H
Comm lag (-1)	0.670***	0.015	0.007	0.620***	0.017	0.001	0.260***	-0.007	-0.000	0.232***	0.059**	0.000
	(10.999)	(0.793)	(0.922)	(12.691)	(1.150)	(0.616)	(3.840)	(-0.242)	(-1.379)	(3.624)	(2.016)	(0.849)
Comm lag (-2)	-0.071	0.013	0.007							-0.054	-0.025	0.000
	(-1.149)	(0.700)	(0.956)							(-0.821)	(-0.854)	(0.188)
Comm lag (-3)										0.134**	0.024	-0.000
										(2.147)	(0.846)	(-1.472)
Comm lag (-4)												
PPI lag (-1)	-0.099	0.247***	0.006	-0.185	0.328***	0.011	0.735***	0.591***	0.005***	0.050	0.227***	0.000
	(-0.516)	(4.294)	(0.248)	(-1.023)	(5.823)	(1.334)	(4.870)	(8.794)	(6.602)	(0.338)	(3.370)	(0.186)
PPI lag (-2)	0.012	0.246***	0.030							0.106	0.170**	0.000
	(0.062)	(4.275)	(1.245)							(0.708)	(2.490)	(0.375)
PPI lag (-3)										0.274*	0.232***	0.000
										(1.760)	(3.270)	(0.792)
PPI lag (-4)												
HICP lag (-1)	-0.765	-0.016	-0.004	1.733	0.422	0.140**	-11.082	-4.088	0.590***	0.828	8.118	0.361***
	(-1.599)	(-0.110)	(-0.068)	(1.378)	(1.078)	(2.347)	(-1.210)	(-1.002)	(14.027)	(0.026)	(0.568)	(5.784)
HICP lag (-2)	0.440	0.215	-0.139**							-1.750	9.338	0.347***
	(0.921)	(1.496)	(-2.328)							(-0.056)	(0.653)	(5.555)
HICP lag (-3)										1.952	-3.919	0.145**
										(0.063)	(-0.276)	(2.338)
HICP lag (-4)												
Constant	0.084	0.082**	0.016	0.063	0.111***	0.013***	0.137	0.133	0.002*	-0.114	-0.175	0.001*
	(0.926)	(2.994)	(1.423)	(0.713)	(4.003)	(3.081)	(0.725)	(1.583)	(1.868)	(-0.347)	(-1.167)	(1.672)
Fuel	0.024	-0.008	0.001	0.024	-0.006	-0.000	0.150***	0.088***	-0.000	0.075	0.023	0.000
	(1.357)	(-1.414)	(0.455)	(1.367)	(-1.053)	(-0.524)	(3.977)	(5.208)	(-0.536)	(1.341)	(0.898)	(0.951)
Fuel(-1)	0.013	0.018***	-0.001	0.009	0.019***	-0.000	-0.044	-0.013	0.000	0.008	0.024	-0.000
	(0.711)	(3.314)	(-0.348)	(0.528)	(3.524)	(-0.237)	(-1.109)	(-0.759)	(1.225)	(0.132)	(0.910)	(-0.442)
Fuel(-2)	-0.005	-0.002	-0.003	-0.004	-0.003	-0.001	-0.037	0.023	0.000	-0.044	-0.027	0.000***
	(-0.250)	(-0.302)	(-1.452)	(-0.198)	(-0.548)	(-0.643)	(-0.964)	(1.309)	(0.768)	(-0.768)	(-1.037)	(3.048)
Fuel(-3)	-0.005	0.005	-0.003	-0.004	0.010	0.001	-0.015	-0.017	-0.000	-0.019	0.015	-0.000
	(-0.264)	(0.881)	(-1.450)	(-0.218)	(1.811)	(1.494)	(-0.382)	(-1.001)	(-0.444)	(-0.336)	(0.565)	(-0.023)
Fuel(-4)	0.013	0.001	0.003	0.011	0.001	-0.001	-0.001	0.028	-0.000	0.064	0.025	0.000
	(0.743)	(0.267)	(1.230)	(0.640)	(0.133)	(-1.341)	(-0.026)	(1.642)	(-0.771)	(1.115)	(0.940)	(1.474)
Fuel(-5)	-0.004	0.001	-0.001	-0.005	0.003	0.001	-0.077**	-0.007	0.000	0.050	-0.012	0.000
	(-0.283)	(0.260)	(-0.257)	(-0.283)	(0.644)	(0.986)	(-2.036)	(-0.403)	(1.134)	(0.879)	(-0.452)	(1.134)
Fuel(-6)	0.029*	0.006	-0.000	0.029*	0.008	-0.001	-0.057	-0.023	0.000	0.058	-0.023	0.000
	(1.694)	(1.215)	(-0.226)	(1.721)	(1.532)	(-1.332)	(-1.510)	(-1.356)	(1.068)	(1.041)	(-0.915)	(0.019)
Summary Statistics												
R-squared	0.442	0.267	0.060	0.436	0.209	0.048	0.368	0.434	0.592	0.166	0.328	0.684
Adj. R-squared	0.416	0.233	0.016	0.416	0.181	0.015	0.345	0.414	0.577	0.118	0.289	0.666
S.E. equation	1.377	0.415	0.172	1.377	0.429	0.065	3.005	1.338	0.014	4.465	2.036	0.009
F-statistic	17.026	7.811	1.372	21.806	7.453	1.430	16.386	21.630	40.898	3.446	8.403	37.388
Log likelihood	-502.26	-150.75	107.31	-503.91	-161.87	389.56	-732.49	-495.51	844.67	-845.43	-615.34	976.93
Akaike AIC	3.524	1.125	-0.637	3.515	1.180	-2.584	5.075	3.457	-5.691	5.887	4.316	-6.552
Schwarz SC	3.700	1.300	-0.461	3.653	1.318	-2.446	5.213	3.596	-5.552	6.100	4.530	-6.339
Mean dependent	0.204	0.198	0.021	0.204	0.198	0.018	0.360	0.318	0.008	0.041	-0.011	0.009
S.D. dependent	1.802	0.474	0.173	1.802	0.474	0.066	3.713	1.748	0.021	4.755	2.414	0.015

Note: Columns are grouped by food (vegetables, fruits, oils & fats and sugar), with three subcolumns for commodity (C), producer price index (P), and consumer price index (H). Coefficients are in the first line (with stars denoting significance levels: * 10%, ** 5%, *** 1%). T-statistic in the second line.

Table B.3: Linear model estimated parameters by food group: coffee, non-alc.beverages, food n.e.c., alcohol & tobacco

	Coffee			Non-alcoholic beverages			Food n.e.c.			Alcohol & tobacco		
	C	P	H	C	P	H	C	P	H	C	P	H
Comm lag (-1)	0.193***	0.018***	0.000	0.662***	0.020	0.000	0.675***	0.035**	-0.000	0.297***	-0.012	-0.002
	(3.17)	(3.25)	(1.39)	(10.94)	(1.05)	(0.01)	(10.99)	(2.32)	(-0.15)	(5.18)	(-1.20)	(-1.09)
Comm lag (-2)	-0.021	0.003	0.000	-0.089	0.035	0.001	-0.177**	0.004	0.001*			
	(-0.34)	(0.52)	(1.43)	(-1.45)	(1.80)	(1.17)	(-2.45)	(0.23)	(1.94)			
Comm lag (-3)	0.006	0.019***	0.000*				0.150**	0.023	-0.000			
	(0.09)	(3.36)	(1.93)				(2.40)	(1.50)	(-0.95)			
Comm lag (-4)	-0.092	0.020***	0.000***									
	(-1.43)	(3.35)	(3.15)									
PPI lag (-1)	1.660**	-0.005	0.005***	0.173	0.080	0.004***	0.018	0.175***	0.006***	-0.001	0.021	-0.014
	(2.44)	(-0.08)	(5.71)	(0.93)	(1.37)	(3.15)	(0.07)	(2.96)	(6.22)	(-0.00)	(0.25)	(-1.12)
PPI lag (-2)	0.141	0.134**	0.002**	0.311	0.255***	0.003**	-0.047	0.117*	-0.000			
	(0.20)	(2.03)	(2.07)	(1.64)	(4.29)	(2.34)	(-0.18)	(1.84)	(-0.20)			
PPI lag (-3)	0.509	0.212***	0.001				-0.028	0.265***	0.001			
	(0.69)	(3.14)	(1.23)				(-0.11)	(4.20)	(0.56)			
PPI lag (-4)	-0.383	-0.013	0.002*									
	(-0.52)	(-0.20)	(1.68)									
HICP lag (-1)	-9.409	14.211***	-0.033	-5.392	1.606	0.248***	4.355	-1.880	0.159**	0.368	-0.031	0.092
	(-0.21)	(1.88)	(-0.53)	(-0.73)	(0.69)	(4.37)	(0.30)	(-0.53)	(2.64)	(0.12)	(-0.06)	(1.10)
HICP lag (-2)	-77.448*	1.542	0.055	-7.813	7.884***	0.362***	-26.371*	6.651**	0.378***			
	(-1.75)	(0.38)	(0.88)	(-1.10)	(3.54)	(6.61)	(-1.94)	(2.01)	(6.74)			
HICP lag (-3)	-34.360	7.552*	0.127**				5.403	4.803	0.170***			
	(-0.78)	(1.88)	(2.06)				(0.39)	(1.44)	(3.00)			
HICP lag (-4)	8.112	-4.315	0.096*									
	(0.20)	(-1.16)	(1.69)									
Constant	0.435	0.044	0.001	0.085	0.041	0.002**	0.149*	0.014	0.000	0.132	0.238***	0.061***
	(1.19)	(1.32)	(1.36)	(0.87)	(1.35)	(2.26)	(1.65)	(0.64)	(0.47)	(0.63)	(6.37)	(10.58)
Fuel	0.029	0.002	0.000	0.020	0.003	0.000	0.015	0.004	-0.000**	0.063*	0.003	0.001
	(0.41)	(0.35)	(0.67)	(1.12)	(0.49)	(0.23)	(0.86)	(0.86)	(-2.32)	(1.91)	(0.54)	(1.16)
Fuel(-1)	0.034	-0.002	0.000	0.012	0.005	0.000	0.019	0.010**	0.000**	0.029	-0.011*	-0.002**
	(0.46)	(-0.26)	(0.72)	(0.69)	(0.94)	(0.21)	(1.04)	(2.28)	(2.13)	(0.86)	(-1.88)	(-1.99)
Fuel(-2)	0.048	-0.002	0.000	-0.007	-0.008	-0.000	-0.019	-0.004	0.000	-0.025	0.007	0.002*
	(0.66)	(-0.36)	(0.13)	(-0.38)	(-1.39)	(-0.39)	(-1.01)	(-0.99)	(0.13)	(-0.74)	(1.23)	(1.74)
Fuel(-3)	-0.069	0.003	0.000	-0.003	0.006	0.000	-0.000	0.003	0.000*	-0.088***	0.000	-0.001
	(-0.95)	(0.49)	(0.89)	(-0.18)	(1.03)	(0.12)	(-0.01)	(0.77)	(1.74)	(-2.59)	(0.05)	(-1.40)
Fuel(-4)	0.011	0.004	0.000	0.013	0.000	0.000	0.009	-0.002	0.000**	0.016	0.005	0.000
	(0.15)	(0.55)	(1.39)	(0.74)	(0.05)	(0.78)	(0.50)	(-0.50)	(2.01)	(0.46)	(0.81)	(0.08)
Fuel(-5)	0.013	0.001	0.000	-0.009	-0.002	0.000	-0.006	0.004	0.000	0.047	0.005	0.001
	(0.18)	(0.12)	(0.19)	(-0.50)	(-0.39)	(0.42)	(-0.36)	(0.96)	(1.31)	(1.40)	(0.79)	(1.28)
Fuel(-6)	0.120*	-0.005	0.000	0.032*	-0.003	0.000	0.037**	-0.006	-0.000	0.000	0.001	-0.000
	(1.69)	(-0.80)	(0.12)	(1.87)	(-0.52)	(-0.54)	(2.21)	(-1.38)	(-0.62)	(0.01)	(0.15)	(-0.36)
Summary Statistics												
R-squared	0.086	0.448	0.559	0.443	0.296	0.504	0.461	0.516	0.767	0.131	0.030	0.041
Adj. R-squared	0.022	0.409	0.528	0.417	0.264	0.481	0.430	0.488	0.753	0.100	-0.004	0.007
S.E. equation	5.706	0.523	0.008	1.376	0.430	0.011	1.361	0.330	0.006	2.674	0.478	0.073
F-statistic	1.347	11.654	18.197	17.089	9.041	21.828	14.763	18.410	56.637	4.233	0.886	1.195
Log likelihood	-915.68	-215.50	1008.35	-502.02	-161.47	924.33	-497.24	-82.36	1112.10	-698.36	-193.81	354.79
Akaike AIC	6.387	1.607	-6.746	3.522	1.198	-6.214	3.510	0.678	-7.475	4.842	1.398	-2.347
Schwarz SC	6.638	1.859	-6.495	3.698	1.374	-6.038	3.724	0.892	-7.262	4.980	1.536	-2.209
Mean dependent	0.488	0.214	0.004	0.204	0.202	0.009	0.204	0.179	0.005	0.233	0.242	0.063
S.D. dependent	5.770	0.681	0.012	1.802	0.501	0.015	1.802	0.462	0.011	2.818	0.477	0.074

Note: Columns are grouped by food (coffee, non-alcoholic beverages, food not elsewhere classified and alcohol & tobacco), with three subcolumns for commodity (C), producer price index (P), and consumer price index (H). Coefficients are in the first line (with stars denoting significance levels: * 10%, ** 5%, *** 1%). T-statistic in the second line.

Table B.4: VECM model estimated parameters (relative price scenarios)

	Scenario 1		Scenario 2	
	D.log_food	D.log_nonfood	D.log_food	D.log_nonfood
Long-Run Dynamics				
Log_nonfood	1.350***		1.352***	
	(0.014)		(0.015)	
Structuralbreak_dummy			0.082***	
			(0.013)	
Constant	-1.622***		-1.630***	
	(0.064)		(0.065)	
Short-Run Dynamics				
Error correction term	-0.070**	0.067**	-0.051	0.103***
	(0.034)	(0.033)	(0.035)	(0.033)
D.log_food (-1)	0.116	0.102	0.182**	0.158*
	(0.102)	(0.100)	(0.089)	(0.085)
D.log_food (-2)			0.281***	-0.128
			(0.085)	(0.081)
D.log_nonfood (-1)	0.284***	0.582***	0.198**	0.345***
	(0.107)	(0.105)	(0.098)	(0.093)
D.log_nonfood (-2)			0.244**	0.234**
			(0.106)	(0.101)
Constant	0.003***	0.003***	0.002*	0.002**
	(0.001)	(0.001)	(0.001)	(0.001)
Summary Statistics				
Long-Run Dynamics				
Observations	97		108	
R-squared	.989		0.99	
Root MSE	.0195		0.222	
Short-Run Dynamics				
Observations	95	95	105	105
R-squared	0.595	0.548	0.422	0.242
Root MSE	0.006	0.006	0.007	0.007

Note: This table shows the estimated coefficients for two scenarios of the food vs. non-food price relationship. Scenario 1: model estimated up to 2022Q1 (no structural break). Scenario 2: model including a break in 2022Q2 (full sample up to 2024Q4), as presented in Section 3.3. Robust standard errors in parentheses. Significance levels: *** $p < 0.01$, ** $p < 0.05$, * $p < 0.1$.

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