Global Food Prices and Inflation

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Structured Abstract

Purpose

This paper aims to examine the role of global food price mean as well as volatility shocks as determinants of domestic food price inflation for a range of countries with different food shares in total consumption and in the CPI basket. The analysis provides useful information to policy makers to control inflation, and also to market participants to develop appropriate investment strategies.

Design/methodology/approach

It uses the endogenous regime switching model with dynamic feedback and interactions developed by Chang et al. (2023) to obtain mean and volatility indicators, and then includes them in structural VAR (Vector Autoregressive) models to assess their impact on inflation. Counterfactual analysis is also carried out.

Findings

The results suggest that both global food price mean and volatility shocks have sizeable effects on food price inflation in all countries and persistent second-round effects on core inflation in most countries. An extension of the analysis using disaggregate global food price data shows that the existence of second-round effects is independent of the size of the response of domestic food inflation to global food price shocks.

Originality

Unlike previous studies, the analysis carefully distinguishes between two types of global food price shocks (namely mean or volatility) and their effects on core inflation, which provides crucial information to monetary authorities to formulate appropriate policy responses and to agents to make investment decisions.

Keywords: Food price mean and volatility, core inflation, endogenous regime-switching, second-round effects

JEL Classification: C13, C58, E31, Q10

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1. Introduction

It is often argued that monetary authorities aiming to achieve price stability should target core rather than headline inflation, since the latter includes highly volatile food and energy prices that introduce noise and are not informative about medium- to long-term inflation trends (Giri, 2022). Indeed, most central banks around the world place greater emphasis on core rather than headline inflation when designing monetary policy. Two issues arise in this context, i.e. exactly how volatile food and energy prices are and to what extent they affect core inflation. While plenty of evidence is available in the case of energy prices (see, for instance, Elder and Serletis, 2010), much less is known about food prices. As stressed by De Gregorio (2012), central banks should not overlook food price inflation since it has significant effects on core inflation. For this reason the present paper aims to provide new, extensive evidence on the inflationary impact of shocks to global food prices and their volatility and to assess their second-round effects on core inflation.

Specifically, we apply the endogenous regime-switching model with dynamic feedback and interactions developed by Chang et al. (2023) to monthly data on the United Nations Food and Agriculture Organization (FAO) nominal food price index from January 1990 to October 2023. The chosen model produces measures of both global food price mean and volatility, where the latter reflects uncertainty and risk in the global food market. Distinguishing between the two is of crucial importance for central banks to adopt appropriate policy responses depending on the type of shock. The estimated mean and volatility indicators are then included in a structural VAR (Vector Autoregressive) model with sign restrictions to assess their effects on domestic food price inflation. Next, counterfactual analysis is used to examine possible second-round effects on core inflation. Finally, further evidence is obtained by using the disaggregate nominal FAO food price indices. The analysis is carried out for eight countries with different food shares of total consumption and in the CPI basket, namely the US, the UK, the euro area, Canada, Japan, South Korea, Mexico and Denmark.

On the whole, this paper makes a fivefold contribution. First, it applies the endogenous regime switching model by Chang et al. (2023) to derive measures of both global food price mean and volatility; this method allows for unsynchronised switches in the mean and volatility, which are determined by latent factors, and for possible feedback from past innovations. Second, it uses the FAO food price index, which measures specifically food prices (both aggregate and disaggregate) as opposed to the overall commodity prices often analysed in other studies (see, e.g., Gelos and Ustyugova, 2017). Third, it performs a VAR analysis with an appropriate identification scheme to examine the effects of global food price mean and volatility shocks. Fourth, it assesses the second-round effects of global food price shocks on core inflation by means of counterfactual analysis. Fifth, it also provides evidence for nominal disaggregate food prices.

The remainder of the paper is structured as follows. Section 2 provides an overview of the relevant literature, Section 3 outlines the modelling framework, Section 4 discusses the empirical results, and Section 5 offers some concluding remarks.

2. Literature Review

Friedman and Schwartz (1963) had famously argued that inflation is a monetary phenomenon, and that therefore the only concern of monetary authorities should be to control the money supply. However, this monetary approach was then superseded by subsequent studies focusing on the role of credibility. In particular, as discussed in Taylor (1993), the central bank needs to decide whether to conduct monetary policy based on a strict rule or exercise discretion, which in recent years has become an ever more important debate in the face of global commodity price shocks. Most existing studies are based on commodity price indices which also include aggregate food prices. For instance, Gelos and Ustyugova (2017) examine the structural characteristics associated with a stronger commodity price pass-through. Their findings suggest that economies with higher overall inflation or a larger food share in the CPI basket are more vulnerable to food price shocks, and also that the adoption of an inflation targeting regime helps to anchor inflation expectations, thereby reducing the second-round effects of food price shocks. Sekine and Tsuruga (2018) estimate the effects of commodity price shocks on headline inflation in a monthly panel of 144 countries and find that any initial effect on inflation disappears within one year, the risk of second-round effects being low.

Gilbert (2010) suggests that historic food price booms were caused by common factors related to demand growth and monetary and financial developments. Studies which examine food prices more directly focus on the pass-through of food price shocks and on appropriate policy responses. For instance, Pourroy et al. (2016) suggest that the optimal monetary policy response to food price shocks depends on the income level, with consumer price inflation targeting being optimal in low income countries, while in high income countries non-food price inflation targeting is more appropriate. Ferrucci et al. (2018) investigate the nonlinear pass-through of food prices to consumer and producer price inflation in the EU, which they find to be partially explained by the Common Agricultural Policy. They also conclude that disaggregate food price data are more informative. The literature concerned with the impact of food prices on core inflation is relatively limited. Pedersen (2011) applies a VAR model with Cholesky decomposition to analyse the effects of food and energy prices on other consumer prices for 46 countries, and finds that food price shocks have stronger ones on core prices than energy price shocks. De Gregorio (2012) uses simple regression analysis to assess the effects of food prices on headline and core inflation and finds that second-round effects on the latter are stronger for countries with a large food consumption share in total consumption.

The literature has reported that a strong connection between food and oil prices, which has been linked to greater biofuel demand. Chen et al. (2010) for instance find that changes in grain prices are strongly influenced by oil prices. Pala (2013) even establishes a long-run cointegrating relationship between oil and food price indices. Olayungbo (2021) instead reports that food price indices in developing countries are important determinants of global oil prices. These findings are particularly relevant in light of the 2007-2008 food price hike which has been linked to the diversion of food commodities into biofuel.

The above discussion of the previous literature indicates the existence of a knowledge gap resulting from the fact that very limited results are currently available on the direct effects of both mean and volatility food shocks on inflation and its core component and on whether or not such shocks also have second-round effects. The present study fills this gap by providing more extensive evidence on these issues and also improves upon earlier ones by using a more appropriate econometric methodology; in particular, the approach taken allows for switches in the mean and volatility to be unsynchronised and also uses a better identification scheme; our results are therefore more informative and reliable than those reported in Sekine and Tsuruga (2018), for example. We also carry out counterfactual analysis to obtain evidence on possible second-round effects extending considerably the work of De Gregorio (2012) on this issue.

3. Empirical Framework

3.1 The unsynchronised endogenous regime switching model

A recently developed model by Chang et al. (2023), known as the unsynchronised endogenous regime-switching model (UERS), allows to extract mean and volatility factors which govern the regime shifts between low and high mean and volatility states. The model takes the following general form:

$$y_t - \mu(s_{m,t}) = \sum_{k=1}^{p} \gamma_k (y_{t-k} - \mu(s_{m,t-k})) + \sigma(s_{v,t}) u_t \tag{1}$$

where y_t is the variable of interest (in our case, the FAO food price index), μ is the mean, σ measures volatility, $s_{m,t}$ and $s_{v,t}$ are the mean and volatility state variables, and u_t are the innovations. In this framework the regime changes are determined by two autoregressive latent factors which are correlated with past innovations of the state-dependent process. As a result, the transition probabilities are time-varying and determined by the lagged values of the time series. The evolution of the state variable $s_{i,t}$ is driven by whether the unobserved latent factors w_{it} are above or below some unknown threshold τ_i:

$$s_{it} = \begin{cases} 0 & if \quad w_{it} \geq \tau_i \\ 1 & if \quad w_{it} < \tau_i \end{cases} \quad for\ i = m, v \tag{2}$$

where the factors $w_{i,t}$ are assumed to follow a zero-mean autoregressive process of order 1:

$$w_{i,t} = A w_{i,t-1} + v_t \tag{3}$$

where $\mathrm{A} = \begin{pmatrix} \alpha_{mm} & \alpha_{mv} \\ \alpha_{vm} & \alpha_{vv} \end{pmatrix}$ and v_t are i.i.d. innovations. The endogenous regime changes arise from the correlation between v_{t+1} and the innovation term u_t of the state-dependent process according to the following correlation matrix:

$$\mathrm{P} = \begin{pmatrix} 1 & \rho'_{vu} \\ \rho_{vu} & \mathrm{P}_{vv} \end{pmatrix} = \begin{pmatrix} 1 & & \\ \rho_{v_m,u} & 1 & \\ \rho_{v_v,u} & \rho_{v_m,v_v} & 1 \end{pmatrix} \tag{4}$$

The evolution of the regime factors $w_{i,t}$ is determined by the dynamic interaction between the two factors, captured by the matrix A, and their contemporaneous correlation, measured by P. If $\alpha_{mv} \neq 0$, the volatility regime factor $w_{v,t}$ helps to predict the mean regime factor $w_{m,t}$. Likewise, if $\alpha_{vm} \neq 0$, $w_{m,t}$ helps to predict $w_{v,t}$. If $\rho_{v_m,u} \neq 0$ ($\rho_{v_v,u} \neq 0$), shocks to past changes in y_t affect endogenously the future transition between the mean (volatility) states. Since the state processes s_{it} are not a Markov chain, one needs to use the modified Markov switching filter by Chang et al. (2021) to account for the endogenous feedback channel and to estimate the model. The two unobserved latent factors (mean and volatility) can be used in the subsequent economic analysis; in the case of food prices they represent respectively an indicator of the average food price and of its volatility.

In order to assess the model performance, we compare its forecasting properties to those of a range of rival specifications using 5-, 10-, and 30-year rolling-windows. The first is the volatility endogenous regime switching model (VERS) developed by Chang et al. (2017), where only the volatility factor is allowed to switch. The second is a standard regime switching model with an exogenous Markov chain (MCRS). The third is the regime switching model with time-varying transition probabilities (TVRS) due to Diebold et al. (1994), where the transition probabilities are logistic functions of a predetermined transition variable z_t. We consider three possible variables for z_t, namely (1) the lagged FOA index (TVRS-FOOD), (2) lagged global inflation (TVRS-INF), and (3) the lagged global output gap (TVRS-IP).[1] The out-of-sample performance of the models is compared using the root mean square error (RMSE) and the relative RMSE, which is calculated as the RMSE of each model divided by that of the VERS and multiplied by 100.

3.2 A VAR model with global food price shocks

In order to assess how global food price mean and volatility shocks are transmitted to domestic prices, we estimate a structural VAR model with the following reduced form representation:

$$X_t = \mu + A(L)X_t + u_t \tag{5}$$

where X_t is a 8×1 vector of endogenous variables which includes domestic food price inflation ($food_t$), domestic core consumer price inflation ($core_t$), domestic output growth

[1] The output gap is measured by applying the Hodrick-Prescott filter to world industrial production data.

(y_t), crude oil prices (oil_t), the real exchange rate (s_t), the policy interest rate (i_t) as well as the global food price mean ($w_{m,t}$) and volatility ($w_{v,t}$) indicators. $A(L) = A_1L+\ldots+A_pL^p$ with $p = 12$, which means that we allow for up to 12 lags in the model. The reduced-form shocks u_t are a linear combination of the structural disturbances ε_t so that $u_t = S^{-1}\varepsilon_t$, where S is the structural impact matrix. The structural VAR model then takes the following form:

$$SX_t = \mu + B(L)X_t + \varepsilon_t \tag{6}$$

We identify seven shocks using sign restrictions, which are detailed in Table 1. A domestic supply shock is a cost-push shock arising from core CPI which reduces output growth but increases both food and core inflation and appreciates the real exchange rate. A domestic demand shock arises from domestic output growth and increases food and core inflation as well as output growth. We assume that demand and supply shocks affect headline inflation, therefore they have an impact on both core inflation and food prices. A global oil price shock lowers output and increases the oil price. A contractionary monetary policy shock reduces food and core inflation, but increases the policy rate. An exchange rate appreciation lowers both inflation and output, but increases the real exchange rate. A global food price mean (volatility) shock is expected to increase both domestic food price inflation and the global food price mean (volatility). The restrictions are placed on the response horizons $h = [0, 1]$.

As a first step, impulse response analysis is carried out. Counterfactual analysis is then performed to assess possible second-round effects on core inflation. There are three reasons to expect their presence. First, many food items are intermediate inputs in the production process of other goods whose prices are included in core inflation, such as starch used in biodegradable plastics or natural fibres used for textiles and building construction; these increase production costs for firms, which are then passed on to consumers. Second, since food is a key component of the consumption basket, its price has significant effects on wage pressures. Third, given their importance for consumers, food prices can strongly influence inflation expectations and the wage setting process. To investigate this issue in the counterfactual analysis we shut off the domestic food price inflation response to the global food price mean and volatility shocks.

3.3 Extended analysis

The main analysis is extended using disaggregate nominal food prices for individual categories (cereal, meat, vegetable oil, sugar and dairy). These results shed light on the relative importance for domestic inflation of the various components of global food prices and of their volatility (Ferrucci et al., 2018).

4. Data and Empirical Results

4.1 Data description

We use monthly data from January 1990 to October 2023. The FAO Food Price Index is obtained from the Food and Agriculture Organization of the United Nations. The analysis is conducted for the US, the UK, the euro area, Canada, Japan, South Korea, Mexico and Denmark. We obtain the core consumer price inflation and the food price inflation series from the Organisation for Economic Co-operation and Development (OECD) Consumer price indices database for all countries. Output growth is calculated using the OECD industrial production total industry series. The oil price is the crude West Texas Intermediate (WTI) one. Real effective exchange rate data and the central bank policy rates are obtained from the Bank for International Settlements (BIS). The world industrial production and world inflation data are the OECD total industrial production index and the OECD total inflation (CPI) series, respectively. All variables are included as annual growth rates, except the policy rates which are in levels. Owing to the unavailability of earlier data, we estimate the VAR model starting in November 1998 for Mexico, in January 1999 for the euro area and in May 1999 for South Korea.

Figure 1 plots the nominal FAO food price index alongside its rate of change (Panel A), calculated as the first difference in the log of the index, as well as its volatility (Panel B), computed using a simple GARCH(1,1) model. The food price series is characterised by several abrupt changes. For instance, food prices experienced a peak during 2007-2008, which was linked to the diversion of food commodities into biofuel. While food prices have remained high since 2007, volatility stayed low for most of the same period, apart from some key events related to the Covid-19 pandemic and the Russian invasion of Ukraine, during which supply chain bottlenecks and reduced wheat and grain availability likely increased overall food price volatility. This suggests that periods of high mean and high volatility do not always coincide, thus motivating the need for a model specification which allows for unsynchronised switches.

4.2 Measures of global food price mean and volatility

Figure 2 displays the extracted mean (Panel A) and volatility (Panel B) factors from the UERS. It can be seen that there were large increases in the volatility factor during the 2008 food crisis, but not the mean factor. The 2010-2012 food crisis was also characterised by high volatility and a low mean, whereas in 2021 and 2022, a period with rapidly increasing food prices, both mean and volatility were high. Rising food prices require central banks concerned with headline as well as core inflation to implement contractionary policies. By contrast, higher volatility is often assumed to be a transitory phenomenon and therefore not to require a policy response. Thus, the correct identification of food price shocks as mean or volatility shocks is crucial for monetary authorities. We report the results of the forecast evaluation exercise in Table 2. As can be seen, the UERS outperforms all rival models in terms of its forecasting performance. On the whole, the evidence presented in this section suggests that the mean and volatility factors extracted from the UERS are suitable to capture the behaviour of global food prices.

4.3 The direct and second-round effects of global food price shocks

Next we examine possible differences in the transmission of global food price shocks between the various countries in our sample which differ in terms of their share of food consumption in total consumption and their share of food in the CPI basket. Mexico has the highest food consumption share in total consumption and the highest food share in the CPI basket, both being around 15 percent higher than in the case of the US. There is little variation in the food consumption share in total consumption in recent years for all countries except South Korea.

Figure 3 (Figure 4) displays the responses of all countries to a global food price mean (volatility) shock. The results suggest that the effects on domestic food price inflation are initially strong and positive (around 0.1 to 0.2 percentage points), and then decline steadily and become negative after six months. The response of core CPI to a global food price mean shock would have been close to zero in all cases if there were no response of food CPI to the global food price mean shock. With the food CPI channel open, core CPI reacts positively with a magnitude of 0.05 to 0.15 percentage points in all cases and the effects are persistent for most countries except Canada and Japan. In the euro area, Mexico, South Korea and Denmark, monetary authorities reduce the policy rate within twelve months after the shock, while in all other countries the response is contractionary, possibly to counteract higher core inflation resulting from second-round effects rather than the direct effects of the global food price mean shock.

There are significant differences in the responses of domestic food CPI to global food price volatility shocks between countries. For instance, while for the UK and Denmark the response seems to be more stable, it shows some strong variation in the case of the euro area, Japan and South Korea, all three of which have on average a higher food consumption share in total consumption and a higher food share in the CPI basket. The response of core CPI is positive and around 0.05 to 0.1 percentage points in all cases, provided that the food CPI channel is open. For the euro area the effect is persistent, as in the case of the US. In the UK and Canada the effect dies out eventually, while in the remaining countries there is greater variation in the response over time.

Unlike previous findings by Gelos and Ustyugova (2017), ours do not seem to suggest that countries with a larger food share in the CPI basket are more vulnerable to food price shocks. Our results are to some extent similar to those of De Gregorio (2012), who reports second-round effects on core inflation, and also those of Pedersen (2011), who finds that a food price shock starts to have significant effects on core inflation after two quarters (we report an increase in the impact after four to six months in many cases). The presence of persistent second-round effects of both global food price mean and volatility shocks on core inflation indicates that food prices can have lasting effects on non-food prices; this suggests that there exists either a strong expectations channel or a strong cost pass-through channel in many countries, which stands in stark contrast to earlier findings by Sekine and Tsuruga (2018). It is also noteworthy that central banks seem to respond more strongly to global food mean rather than volatility shocks (although the response to the latter type of shocks increases in the presence of second-round effects on core inflation). This is consistent with their dismissing the volatile behaviour of food prices when formulating policies and focusing instead on their long-run trends in accordance with their rules-based policy (Taylor, 1993).

4.4 Extensions to the analysis using disaggregate food prices

In this section we present the results of an extension to the analysis using the nominal disaggregate FAO food price indices, which are displayed in Figures 5-9. The most persistent second-round effects on core inflation are caused by vegetable oil price mean shocks, while cereal price volatility shocks have highly volatile effects. On average, the second-round effects of the disaggregate shocks are smaller than those of the aggregate ones. Finally, the second-round effects appear to be persistent regardless of the level of aggregation of the data, while their size is dependent on that of the response of food CPI to the aggregate and disaggregate global food price mean and volatility shocks.

5. Conclusions

This paper uses the unsynchronised endogenous regime switching model with dynamic feedback and interactions developed by Chang et al. (2023) to extract global food price mean and volatility factors based on the United Nations Food and Agriculture Organization (FAO) nominal food price index. The chosen specification is shown to outperform a range of competing models in terms of its out-of-sample forecasting properties. A structural VAR model is then estimated to assess the importance of the pass-through of shocks to the obtained global food price mean and volatility indicators to domestic food price inflation in a range of countries with different food consumption shares out of total consumption and different food shares in the CPI basket. Further, counterfactual analysis is conducted to assess the effects of the two types of shocks on core inflation. Finally, the analysis is extended by re-estimating the models using the disaggregate nominal FAO food price indices.

The findings can be summarised as follows. First, the estimated endogenous regime-switching specification allowed us to construct global food price mean and volatility indicators, the latter capturing in particular the likelihood of volatility (a measure of uncertainty in the global food market) remaining in the same regime for long periods of time. Second, the results obtained from the structural VAR models show that domestic food consumer price inflation reacts strongly to global food price mean and volatility shocks, but these effects are only transitory. Third, there is evidence that global food price mean and volatility shocks affect core inflation through second-round effects of domestic food consumer price inflation; these are highly persistent and even increasing over time in most countries, especially in the case of mean shocks. This implies that food price inflation can affect non-food price inflation as a result of shocks originating from global food prices. In contrast to previous studies such as De Gregorio (2012), we find that the food consumption share in total consumption or the food share in the CPI basket of individual countries do not play a role in terms of the existence or size of second-round effects. Fourth, it appears that central banks react more to global food price mean shocks than to volatility ones when designing policies to target inflation. Finally, the results based on disaggregate food prices suggest that the second-round effects on core inflation are persistent regardless of the level of aggregation of the data, which only affects the size of the effects.

These findings have important implications for policymakers. More specifically, our analysis highlights the importance of distinguishing between the effects of global food price mean and volatility shocks, which require different policy responses and can help central banks choose the best measure of consumer price inflation to target. Furthermore, the presence of persistent second-round effects on core inflation implies that there is a strong pass-through channel, either through inflation expectations or firms' mark-up, which is important for central banks to take into account. The results provide insights into the transmission of global shocks and represent useful information for policymakers to identify their temporary and permanent effects. Future research should focus upon obtaining more evidence on the channels through which such effects are transmitted.

Finally, regarding the implications of our findings for market participants and society as a whole, it is clear that successful investment strategies should take into account the fact that, although mean and volatility shocks appear to have a different impact, they both have persistent second-round effects on core inflation. Therefore, when making portfolio choices to manage risk, market participants should be aware that in the presence of such shocks they will be facing high and volatile inflation over a long time horizon, and thus adopt appropriate immunisation strategies for hedging purposes. In the circumstances one would expect a more cautious approach towards investment for society as a whole.

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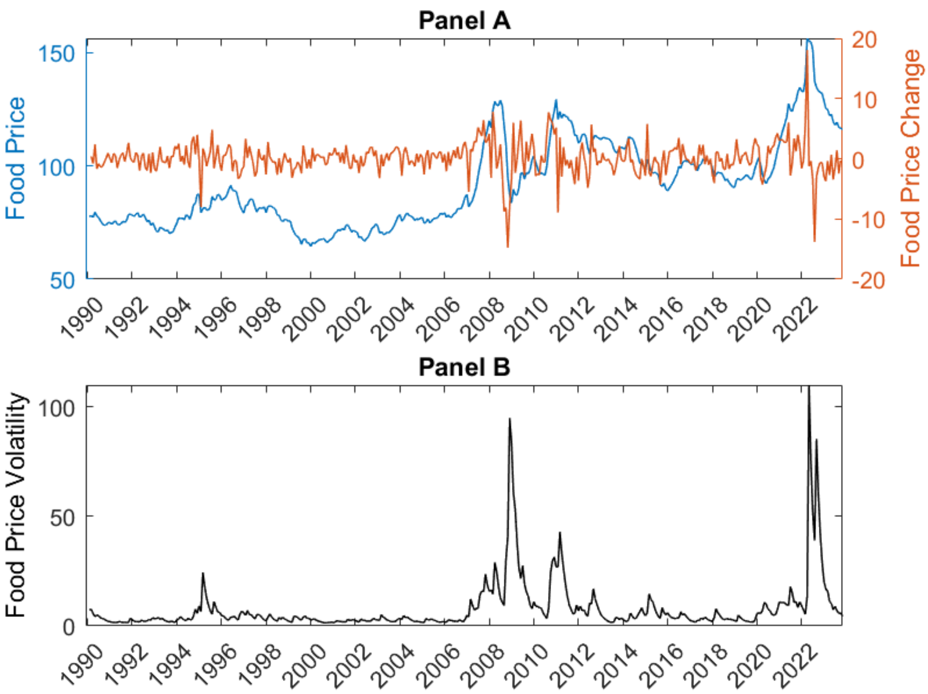
Figures and Tables for "Global Food Prices and Inflation"

Table 1. Sign restrictions in the VAR model

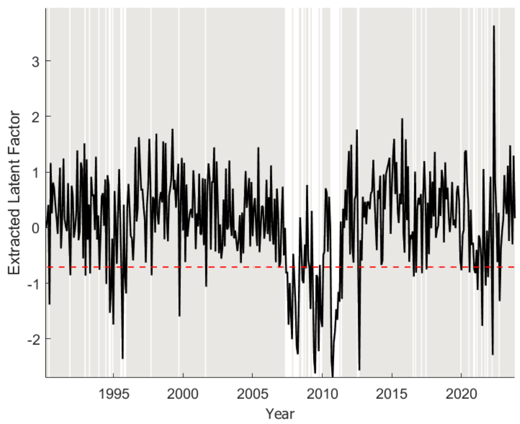
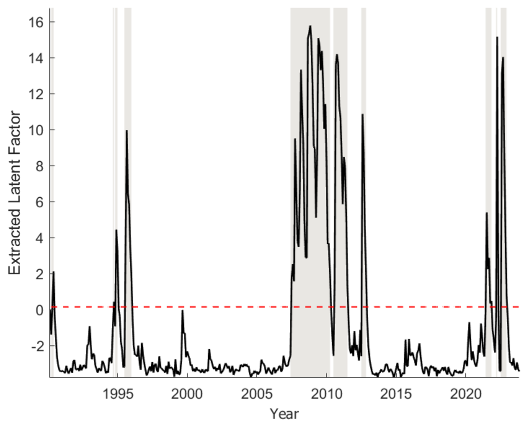
	Supply	Demand	Oil price	Monetary policy	Exchange rate	Food price mean	Food price volatility
$food_t$	+	+		−	−	+	+
$core_t$	+	+		−	−		
y_t	−	+	−		−		
oil_t			+				
s_t	+				+		
i_t				+			
$w_{m,t}$						+	
$w_{v,t}$							+

Notes: Sign restrictions with (+) indicating a positive response to the shock and (−) indicating a negative response.

Figure 1. Global food price and volatility



Notes: Panel A shows the food price index (blue line) and rate of growth over time (orange line), while Panel B displays the conditional volatility of the food price index.

Figure 2. Extracted factors from the UERS	
Panel A – Mean factor	Panel B –Volatility factor
	

Notes: The extracted factors are represented by the black line while the estimated threshold is depicted by the red dashed line. The grey shaded areas indicate periods of high mean (Panel A) and high volatility (Panel B).

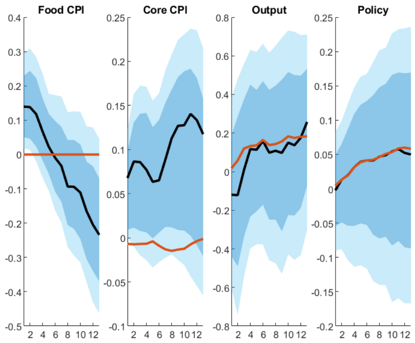
Table 2. Forecast comparison

	UERS	VERS	MCRS	TVRS-FOOD	TVRS-INF	TVRS-IP
5-year window						
RMSE	0.0014	0.0041	0.0019	0.0023	0.0025	0.0025
Relative RMSE	34.15	100.00	46.34	56.10	60.98	60.98
10-year window						
RMSE	0.0015	0.0041	0.0020	0.0024	0.0025	0.0025
Relative RMSE	36.59	100.00	48.78	58.54	60.98	60.98
30-year window						
RMSE	0.0015	0.0042	0.0020	0.0024	0.0026	0.0026
Relative RMSE	35.71	100.00	47.62	57.14	61.90	61.90

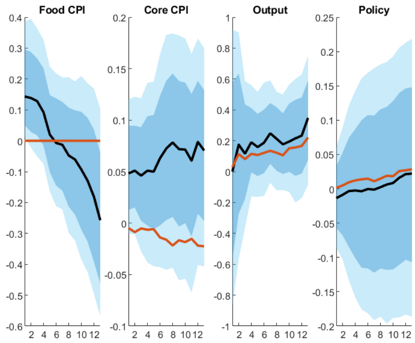
Notes: Forecast comparison based on one-step-ahead forecasts.

Figure 3. Responses to food price mean shocks

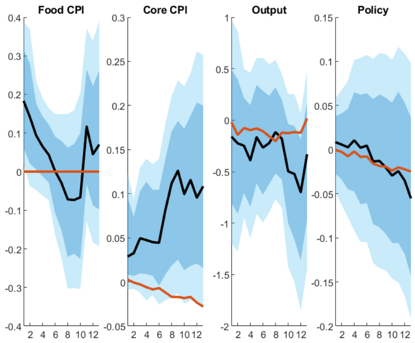
Panel A – US response



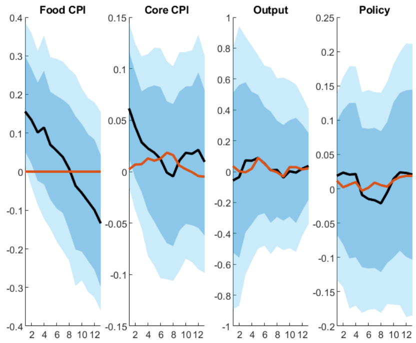
Panel B – UK response



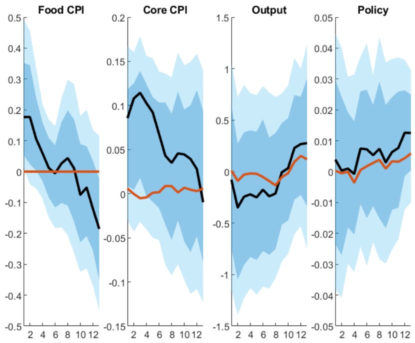
Panel C – Euro area response



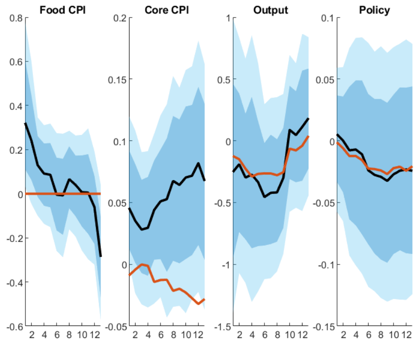
Panel D – Canada response



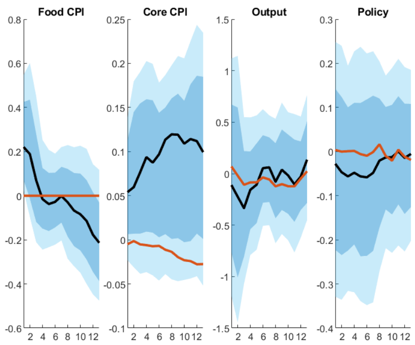
Panel E – Japan response



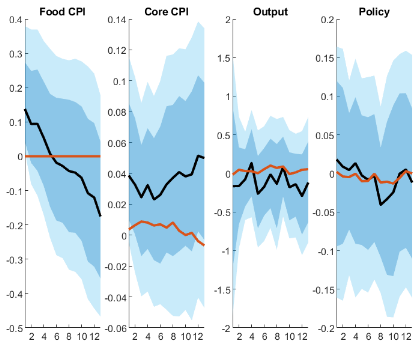
Panel F – South Korea response



Panel G – Mexico response



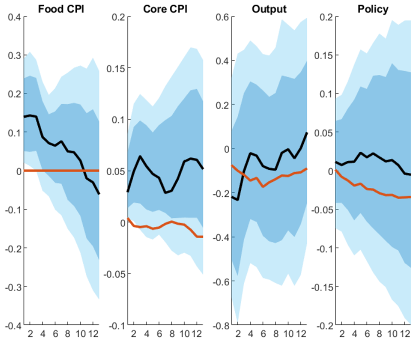
Panel H – Denmark response



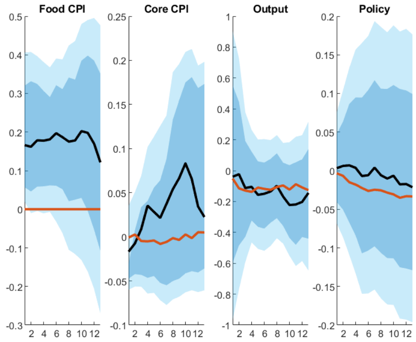
Notes: The solid black line represents the median response, the dark blue shaded area represents the 68% confidence band, while the light blue shaded areas represent the 95% confidence bands. The solid orange line represents the counterfactual with the domestic food inflation channel shut off. All responses are in percentage points.

Figure 4. Responses to food price volatility shocks

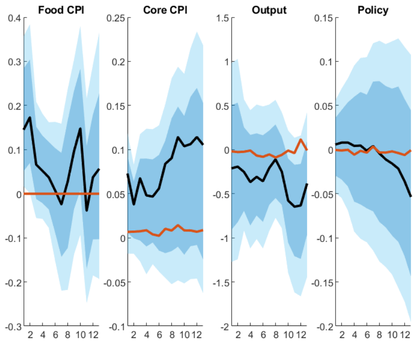
Panel A – US response



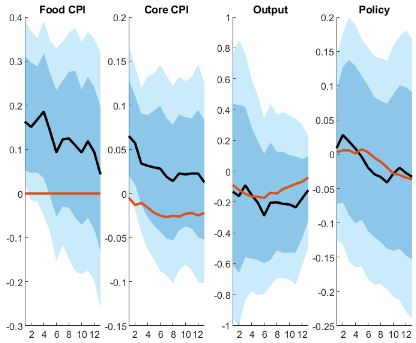
Panel B – UK response



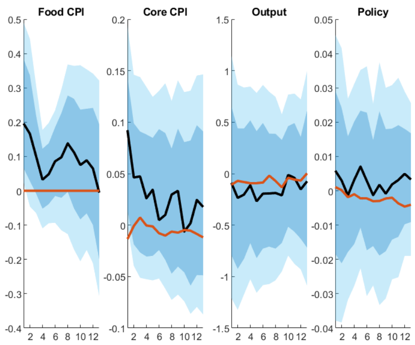
Panel C – Euro area response



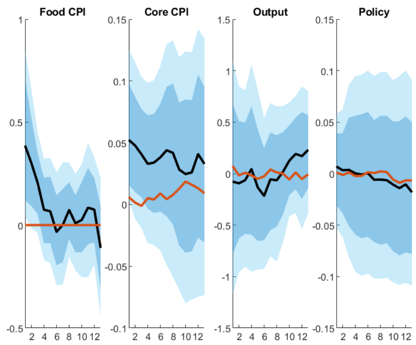
Panel D – Canada response



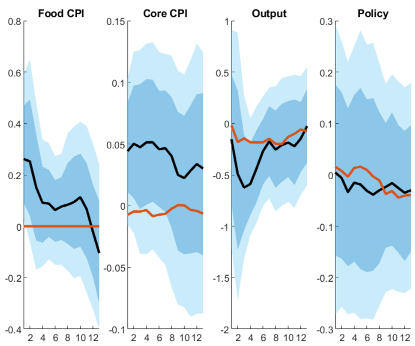
Panel E – Japan response



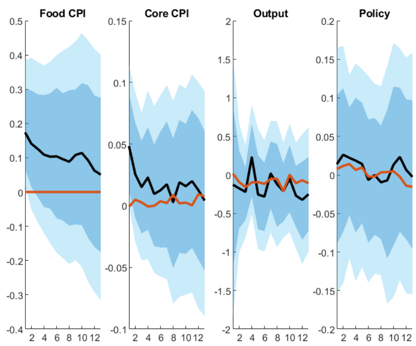
Panel F – South Korea response



Panel G – Mexico response



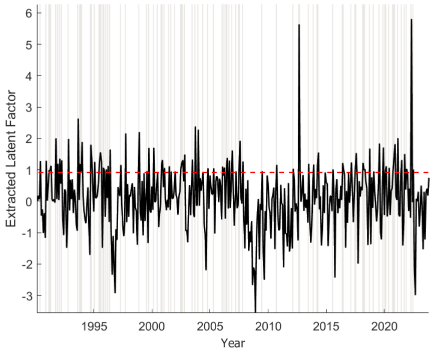
Panel H – Denmark response



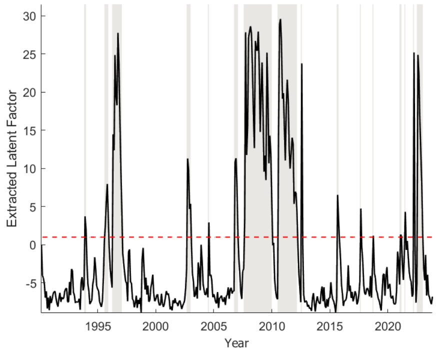
Notes: The solid black line represents the median response, the dark blue shaded area represents the 68% confidence band, while the light blue shaded areas represent the 95% confidence bands. The solid orange line represents the counterfactual with the domestic food inflation channel shut off. All responses are in percentage points.

Figure 5. Results using the cereal price index

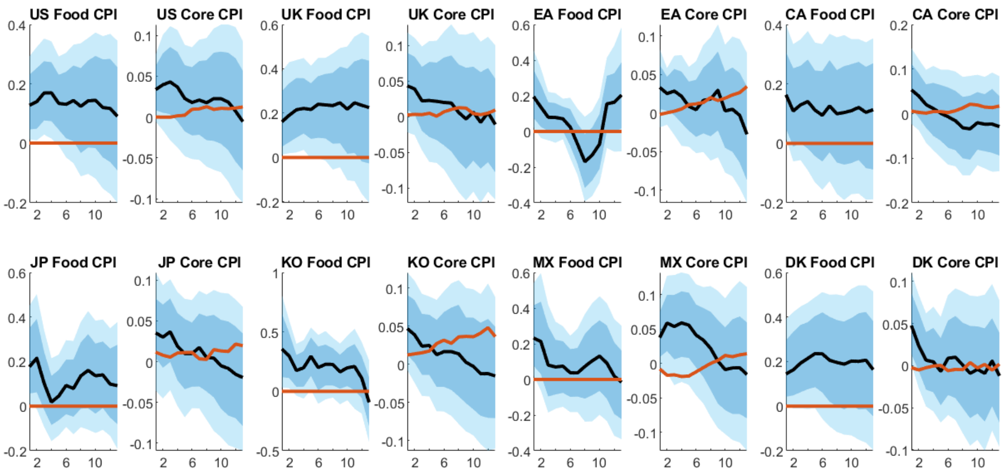
Panel A – Cereal price mean factor



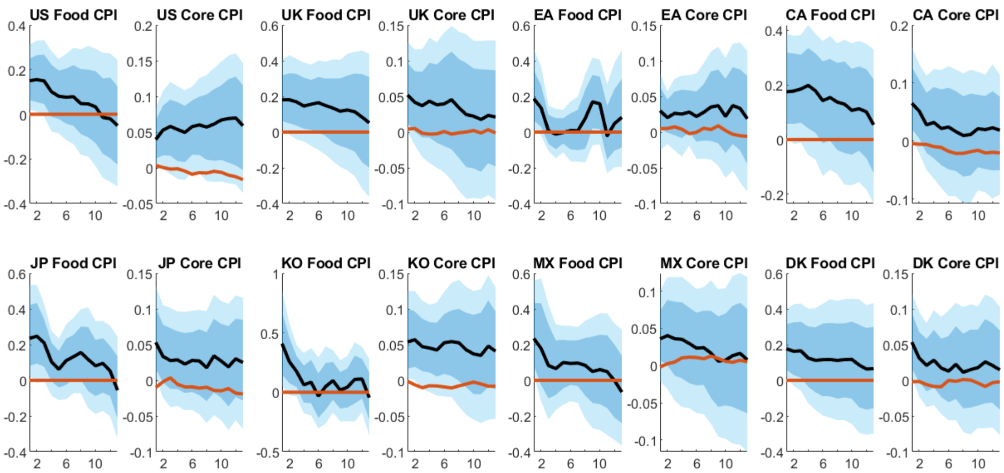
Panel B – Cereal price volatility factor



Panel C – Inflation responses to cereal price mean shock



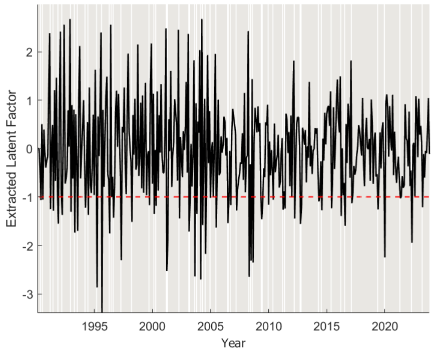
Panel D – Inflation responses to cereal price volatility shock



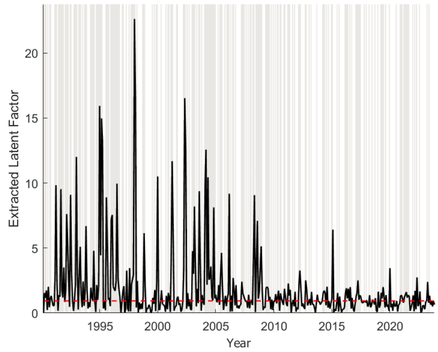
Notes: Panel A and B: The extracted factors are represented by the black line while the estimated threshold is depicted by the red dashed line. The grey shaded areas indicate periods of high mean (Panel A) and high volatility (Panel B). Panel C and D: The solid black line represents the median response, the dark blue shaded area represents the 68% confidence band, while the light blue shaded areas represent the 95% confidence bands. The solid orange line represents the counterfactual with the domestic food inflation channel shut off. US = United States; UK = United Kingdom; EA = euro area; CA = Canada; JP = Japan; KO = South Korea; MX = Mexico; DK = Denmark.

Figure 6. Results using the meat price index

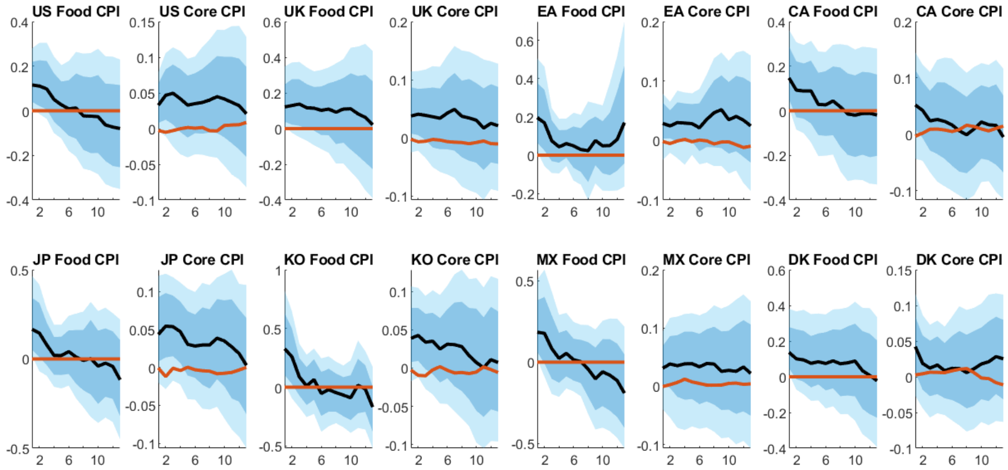
Panel A – Meat price mean factor



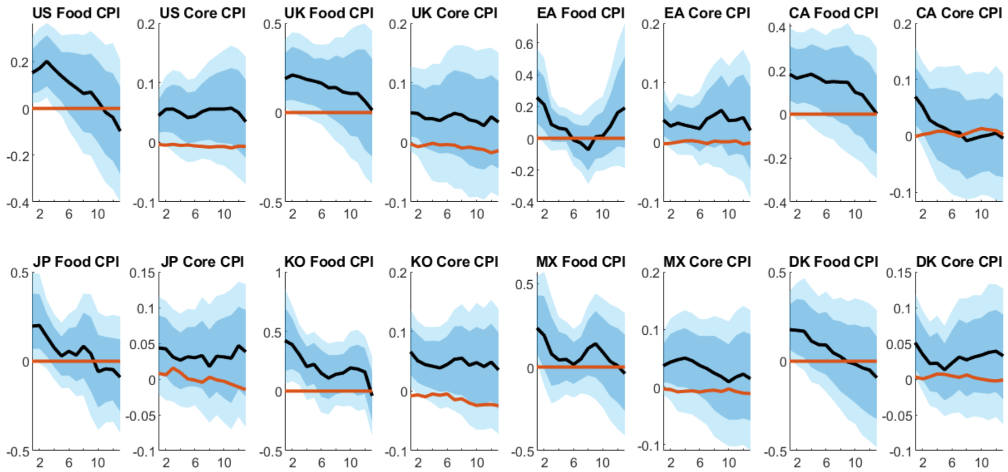
Panel B – Meat price volatility factor



Panel C – Inflation responses to meat price mean shock



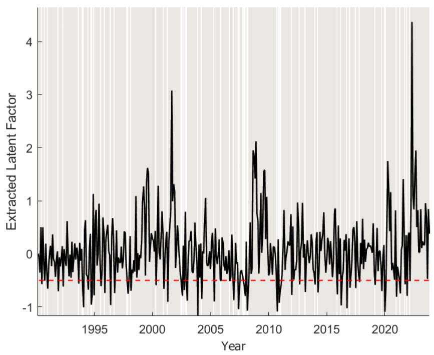
Panel D – Inflation responses to meat price volatility shock

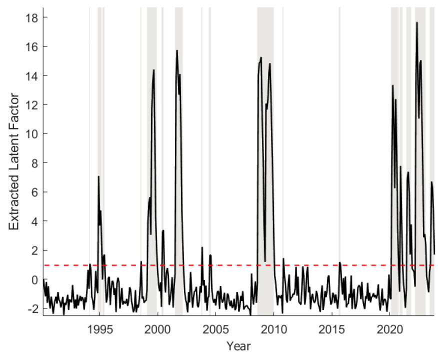


Notes: Panel A and B: The extracted factors are represented by the black line while the estimated threshold is depicted by the red dashed line. The grey shaded areas indicate periods of high mean (Panel A) and high volatility (Panel B). Panel C and D: The solid black line represents the median response, the dark blue shaded area represents the 68% confidence band, while the light blue shaded areas represent the 95% confidence bands. The solid orange line represents the counterfactual with the domestic food inflation channel shut off. US = United States; UK = United Kingdom; EA = euro area; CA = Canada; JP = Japan; KO = South Korea; MX = Mexico; DK = Denmark.

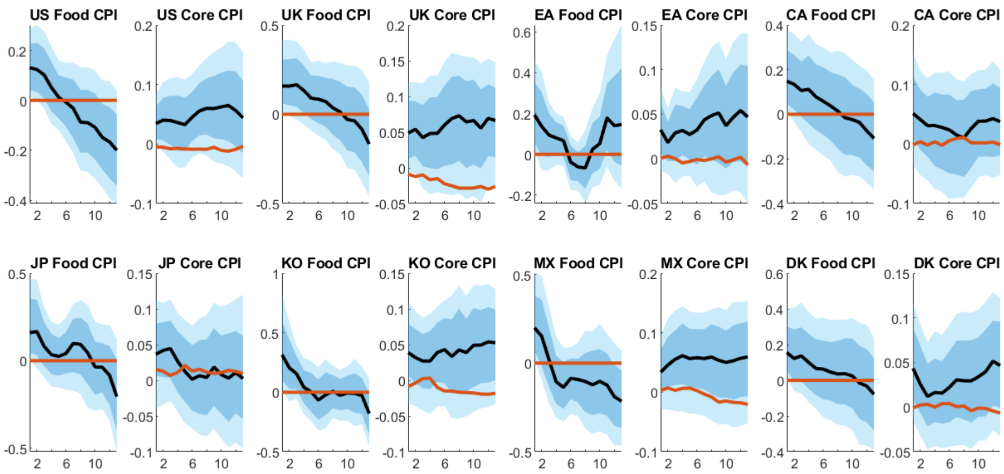
Figure 7. Results using the vegetable oil price index

Panel A – Vegetable oil price mean factor	Panel B – Vegetable oil price volatility factor

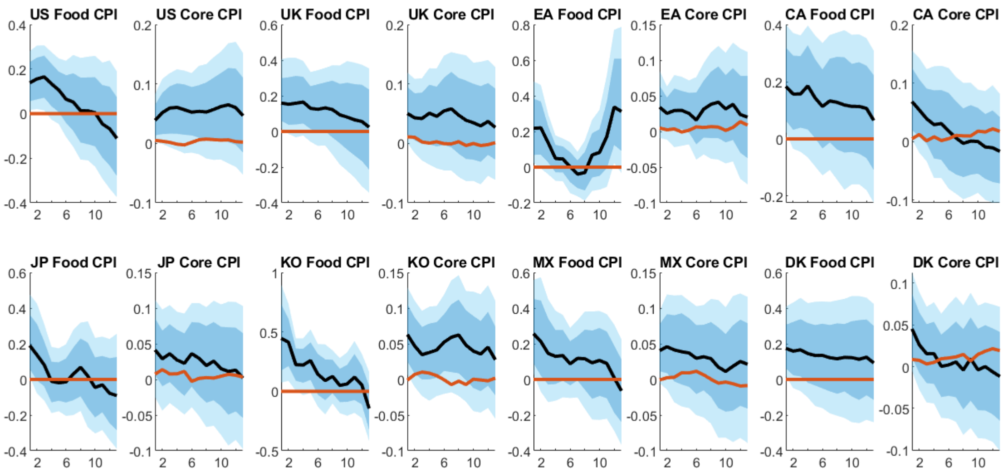




Panel C – Inflation responses to vegetable oil price mean shock

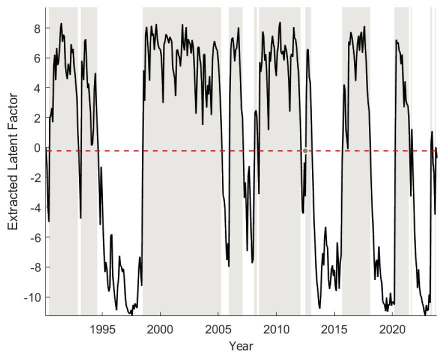
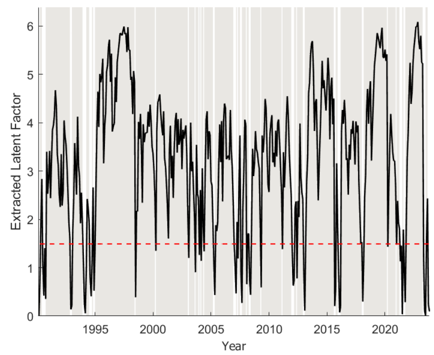


Panel D – Inflation responses to vegetable oil price volatility shock

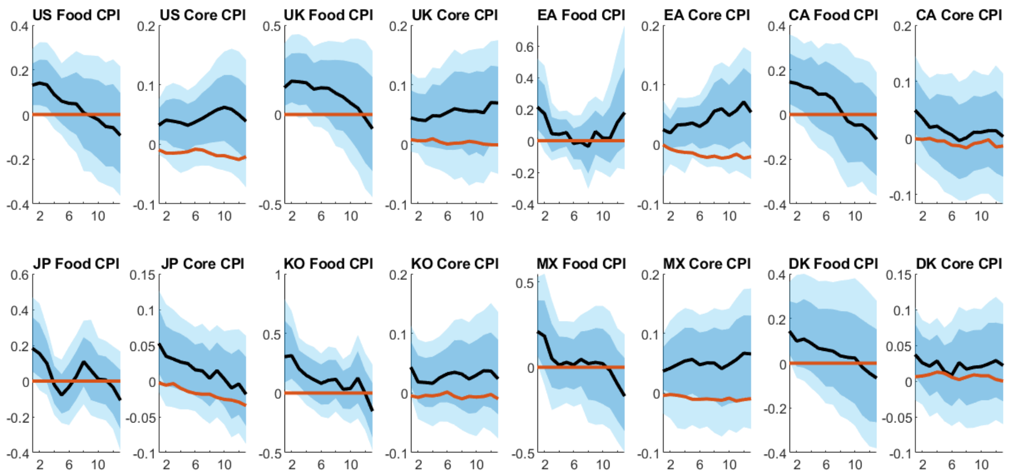


Notes: Panel A and B: The extracted factors are represented by the black line while the estimated threshold is depicted by the red dashed line. The grey shaded areas indicate periods of high mean (Panel A) and high volatility (Panel B). Panel C and D: The solid black line represents the median response, the dark blue shaded area represents the 68% confidence band, while the light blue shaded areas represent the 95% confidence bands. The solid orange line represents the counterfactual with the domestic food inflation channel shut off. US = United States; UK = United Kingdom; EA = euro area; CA = Canada; JP = Japan; KO = South Korea; MX = Mexico; DK = Denmark.

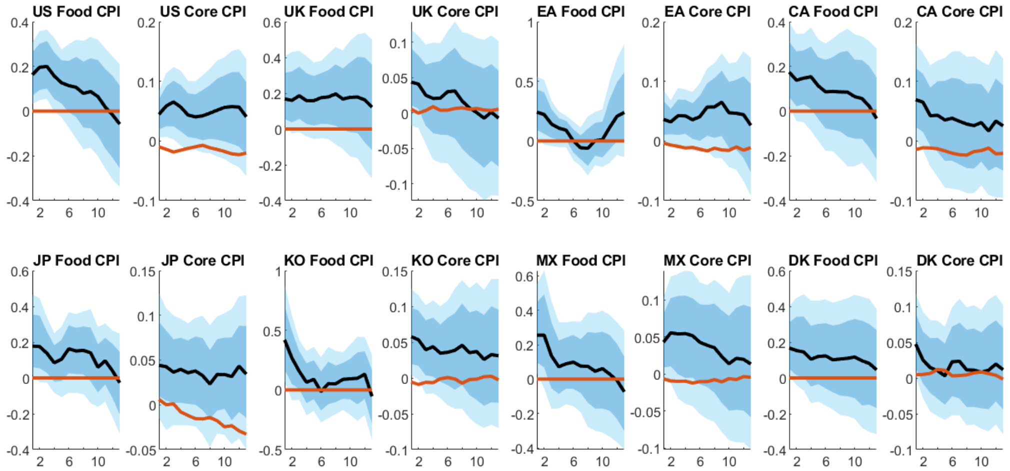
Figure 8. Results using the sugar price index

Panel A – Sugar price mean factor	Panel B – Sugar price volatility factor
	

Panel C – Inflation responses to sugar price mean shock



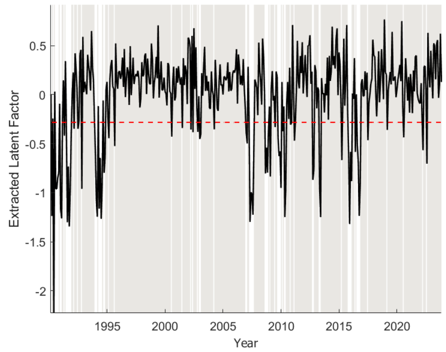
Panel D – Inflation responses to sugar price volatility shock



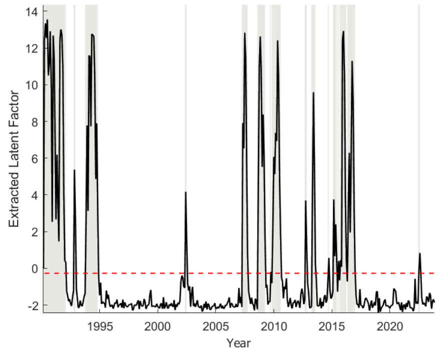
Notes: Panel A and B: The extracted factors are represented by the black line while the estimated threshold is depicted by the red dashed line. The grey shaded areas indicate periods of high mean (Panel A) and high volatility (Panel B). Panel C and D: The solid black line represents the median response, the dark blue shaded area represents the 68% confidence band, while the light blue shaded areas represent the 95% confidence bands. The solid orange line represents the counterfactual with the domestic food inflation channel shut off. US = United States; UK = United Kingdom; EA = euro area; CA = Canada; JP = Japan; KO = South Korea; MX = Mexico; DK = Denmark.

Figure 9. Results using the dairy price index

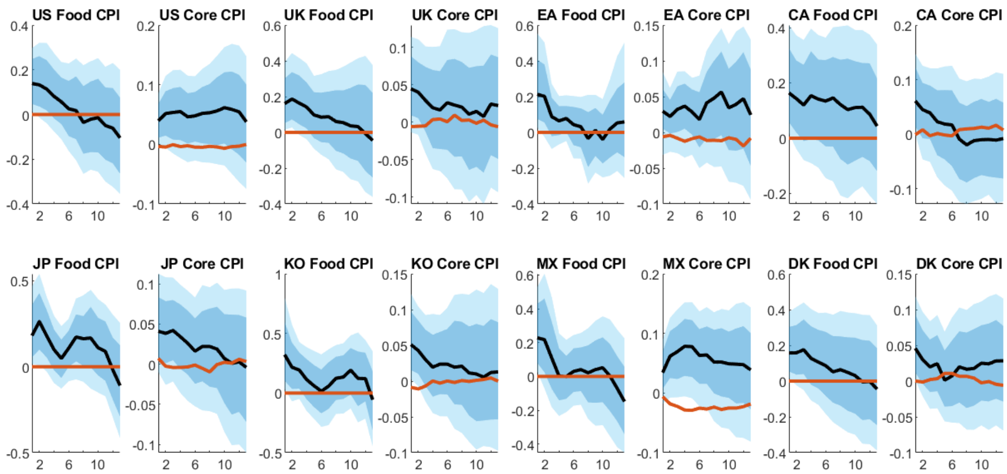
Panel A – Dairy price mean factor



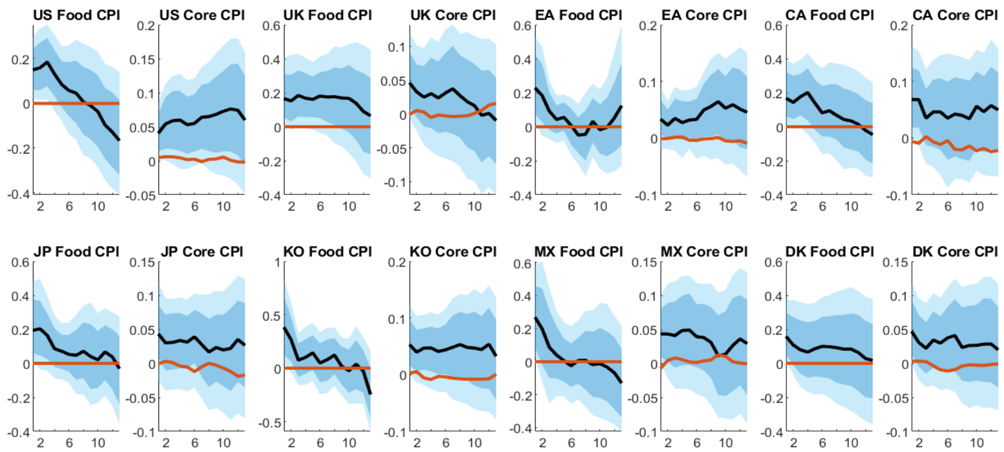
Panel B – Dairy price volatility factor



Panel C – Inflation responses to dairy price mean shock



Panel D – Inflation responses to dairy price volatility shock



Notes: Panel A and B: The extracted factors are represented by the black line while the estimated threshold is depicted by the red dashed line. The grey shaded areas indicate periods of high mean (Panel A) and high volatility (Panel B). Panel C and D: The solid black line represents the median response, the dark blue shaded area represents the 68% confidence band, while the light blue shaded areas represent the 95% confidence bands. The solid orange line represents the counterfactual with the domestic food inflation channel shut off. US = United States; UK = United Kingdom; EA = euro area; CA = Canada; JP = Japan; KO = South Korea; MX = Mexico; DK = Denmark.