Domestic inflation dynamics in the face of changes in international commodity prices, inflation expectations, and the exchange rate*

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Abstract

Recent domestic and global shocks, especially the extraordinary increase in international food and energy prices, as well as the persistent depreciation of the local currency, explain the unusual surge in inflation during the post-pandemic recovery. This study seeks to quantify these factors' contribution to multiple inflation metrics using a Bayesian approach that is robust to the features of a small open economy such as Peru. Structural shocks are identified using a scheme of contemporaneous zero-sign constraints. The results confirm the significant contribution of food and energy price increases, together with exchange rate depreciation, to the recent inflationary episode. This may be associated with the impact of these prices on domestic production costs by increasing the cost of multiple imported inputs. Finally, a counterfactual exercise shows that, had pre-pandemic commodity price forecasts materialized, domestic inflation metrics would not have exceeded the inflation target range.

Abstract

Eventos recientes en el ámbito internacional y doméstico podrían explicar el incremento inusual de la inflación registrado durante la recuperación económica posterior al choque COVID-19. Entre estos eventos, destacan el incremento notable de las cotizaciones internacionales de *commodities* de alimentos y de energía, y la persistente depreciación de la moneda local. En línea con ello, el presente estudio busca cuantificar la contribución a la inflación de estos eventos. Para ello se utiliza un enfoque bayesiano de series de tiempo multivariadas robusto a las características de una pequeña economía abierta como la peruana. En este ejercicio, la dinámica estructural se identifica sobre la base de un esquema de restricciones contemporáneas de signos y ceros. Así, se identifica una contribución significativa e importante de las cotizaciones internacionales de *commodities* de alimentos y de energía, y del tipo de cambio sobre el reciente episodio de alta inflación durante la segunda mitad de 2021. Ello estaría asociado al impacto de dichos precios sobre los costos de producción domésticos mediante el encarecimiento de distintos insumos importados. Finalmente, mediante un ejercicio contrafactual, se estima que si las proyecciones pre-COVID-19 de las cotizaciones internacionales se hubiesen materializado, lo más probable es que ninguna de las medidas domésticas de inflación habrían excedido el rango meta de inflación.

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1 Introduction

After four consecutive years within the target band, inflation in Peru climbed to highs not seen since 2009 (an annual 6.43% as of December 2021). Although the current debate considers both external and domestic factors, the mainstream narrative links the recent surge in domestic inflation to world inflation combined with a considerable nominal depreciation in 2021.[1] However, considerable uncertainty remains regarding the true dynamics underlying the current inflation process. Especially, the monetary authority needs to identify the quantitative contribution of each possible driver of inflation and, accordingly, design an appropriate and timely policy response.

Potential external factors propelling inflation include, in particular, soaring international food and energy prices since 2020. On the domestic front, nominal depreciation accelerated and inflation expectations exceeded the target band for the first time in several years. Both kinds of events translate (directly or indirectly) into domestic inflation and feed back into inflation expectations.

Figure 1 shows that the recent behavior of commodity prices is unusually pronounced and uneven. For instance, following an average 5.5% contraction in 2019 and 2020, annual energy price growth peaked at 171,6% in April 2021. International food and industrial metal prices also showed growth rates not seen since the 2010 commodity supercycle.

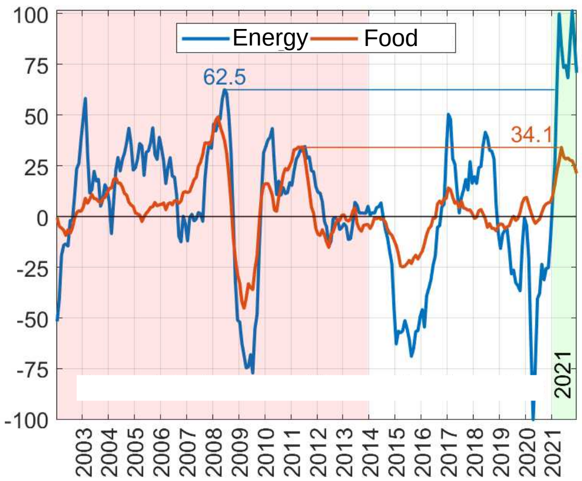
The recent dynamics of international food and energy prices seems to be linked to production bottlenecks, which created a demand/supply mismatch in a context of rapid global recovery in 2021, when several industries reopened once the 2020 pandemic crisis receded. Regarding the transmission channel, these price increases are expected to weigh on domestic marginal production costs, in turn feeding into inflation.

On the domestic side, nominal depreciation accelerated amid mounting inflation expectations (Figure 2). The monthly average exchange rate jumped 11.6% in January-December 2021 and inflation expectations rose to 3.68% as of end-2021. Moreover, the COVID-19 pandemic triggered simultaneous demand and supply shocks across industries, which generated a higher relative demand for food and energy (at the wholesale and retail levels), thereby contributing to higher inflation in 2021 (Figure 2). This higher relative demand was also present across wholesale and retail markets for goods and services other than food and energy.

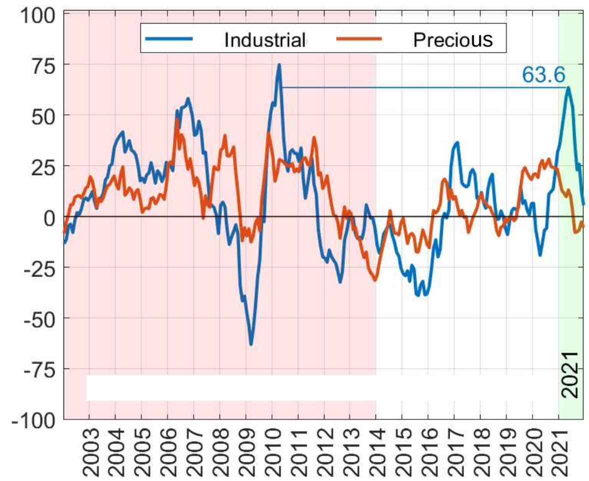
[1] Global inflation was caused by a rapid recovery associated with softer pandemic-related containment measures and soaring transportation costs in international trade. Economic recovery created demand/supply mismatches in several industries, in turn creating bottlenecks in global supply chains.

Figure 1. *Year-on-year variation of international commodity prices*

(a) *Non-Metals*



(b) *Metals*



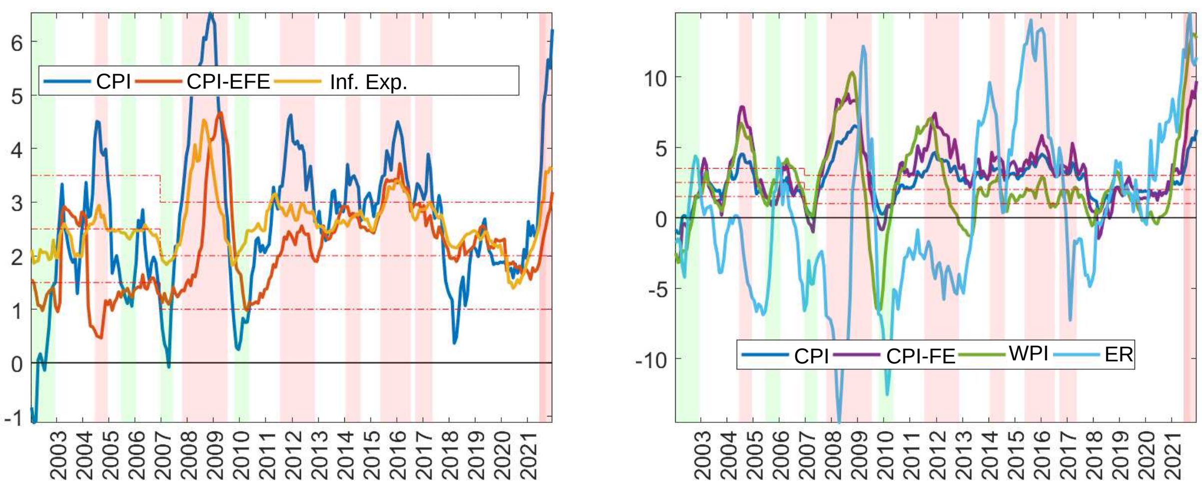
It is likely that the events described above had a significant impact on Peru's inflation performance in 2021. Along these lines, **this study seeks to quantify their contribution to recent inflation dynamics** using a vector autoregressive (VAR) model with an exogenous block, as proposed by Canova (2005); i.e., in the autoregressive vector, the domestic sector is influenced by the dynamics of the external block, but not vice versa. Therefore, the model is consistent with the assumption that Peru is a small, open, price-taking economy.[2] The external block is made up of international food, energy, and (precious and industrial) metal prices; and the domestic block comprises domestic inflation metrics like the consumer price indices for food and energy and excluding those items, wholesale price indices, the exchange rate, and inflation expectations.

We estimate the model using Bayesian econometrics, where three prior coefficient distributions coexist. We include the Minnesota prior, as proposed by Litterman (1986), which assumes that the autoregressive vector is made up of independent random walks (white noises). We also consider the prior proposed by Doan, Litterman, & Sims (1984), which generalizes the Minnesota prior by assuming that the random walks (white noise) in the autoregressive vector are jointly distributed. Finally, we include the arbitrary initial observation prior suggested by Sims (1993), which assigns the cointegration structure to the variables in the autoregressive vector. The hyperparameters comprising these priors are selected such as to maximize the marginal likelihood of the data. This combination of prior structures improves the model's predictive capacity, as reported by Doan, Litterman, & Sims (1984), Sims (1993), and more recently by Bańbura, Giannone, & Reichlin (2010). It should be noted that the Minnesota prior is modified so as to make the Bayesian estimation consistent with an exogenous block of international variables in terms of the lag structure considered in the model. Additionally, the identification method assumes that the domestic block does not have a contemporaneous impact on the external block, thereby completing the assumption of a small open economy.

[2] Canova (2005) uses the exogenous block to identify the impact of U.S.-originated shocks on Latin American economies. U.S. variables affect Latin American countries' domestic performance, but not vice versa.

Figure 2. *Year-on-year domestic inflation rate*

(a) *CPI, CPI-EFE y Infl. Exp.* **(b)** *CPI-FE, WPI and exchange rate*



Note. CPI: Consumer Price Index; CPI-EFE: CPI Ex Food & Energy; CPI-FE: CPI for Food & Energy; and WPI: Wholesale Price Index.

We use a scheme of contemporary sign and zero restrictions, based on the methodology developed by Arias, Rubio-Ramírez, & Waggoner (2018), to identify structural shocks. The zero restrictions are mainly associated with the international commodity prices in the exogenous block. For their part, sign restrictions are imposed only on contemporaneous interactions between variables in the domestic sector. Such restrictions are based on the simultaneity, derived from the the new Keynesian model, between price indices and expectations. We also add restrictions consistent with the evidence of a positive exchange rate pass-through into price indices. It is important to note that we employed the BEAR toolbox developed by Dieppe, Legrand, & Van Roye (2018) to implement the statistical methodology used in this document.

We highlight that, in this research, the autoregressive vector includes data on international and domestic prices, but not on economic activity. This can be considered a limitation as, according to economic theory, assessing the interaction between economic activity and price variables may be instrumental in identifying demand/supply shocks. However, the fluctuation in economic activity variables has been unusually high since 2020 due to pandemic-related disturbances, which could distort the estimations. It is worth mentioning that the addition of economic activity estimations that are robust to this exceptional variability will be addressed in our future research agenda.[3]

The results suggest that it is possible to identify significant increases in domestic inflation in response to international food and energy price shocks. In contrast, international (industrial and precious) metal price shocks cause deflationary and non-significant effects in most periods. For their part, exchange rate shocks produce less persistent inflation responses than international price shocks; and inflation expectations shocks do not seem to affect the behavior of domestic inflation indicators. This result seems to validate the notion that the formation of expectations in this system is profoundly endogenous; and that unexpected variations are simply noise, devoid of information relevant to any measure of inflation.

This pattern suggests that non-metal price fluctuations largely explain the episodes where inflation departed

[3] The literature on this issue is still work in progress, although there are already important developments like Lenza & Primiceri (2020).

systematically from the target band (particularly October 2007-June 2009 and July 2011-October 2012). However, during the last inflation episode in the sample (June-December 2021), currency depreciation, together with international food and energy prices, seem to have played an important role. We underscore that there have been episodes where depreciation and inflation expectations contributed significantly (by more than 50%) to the deviation of inflation from the center of the target band, while international commodity prices had a negative contribution (e.g., in May 2015-June 2016 and September 2016-May 2017).

Similarly, building on the structure of the model, we estimate the domestic inflation that would have materialized in 2020 y 2021 if commodity prices had followed the pattern anticipated before the pandemic breakout. The exercise suggests, with a 68% credible interval, that neither CPI-EFE (CPI Ex Food & Energy) inflation nor inflation expectations would have exceeded the target band. For their part, central estimations for all other measures of inflation (including the CPI) would have remained within the target band and the risk of drifting outside it would have been considerably lower.

These results are consistent with findings in similar studies. Cecchetti & Moessner (2008), Baek & Koo (2010), Durevall, Loening, & Birru (2013), Ferrucci, Jiménez-Rodrıguez, & Onorantea (2012), Sekine & Tsuruga (2018), Lin & Xu (2019), and Chen, Zhu, & Li (2020) explore these kinds of issues in several advanced and emerging economies. They conclude that the contribution of food price variations to headline inflation is greater than that of energy price variations.[4] This result seems to be linked to the greater persistence of international food price variations. These studies also find that core inflation takes longer to revert to its mean, which is consistent with the important persistence of CPI-EFE inflation identified for Peru in this study. At the same time, García-Germán, Bardají, & Garrido (2016) find opposite results for the European Union (i.e., a limited and temporary impact of international food price changes on domestic inflation). However, these results are heterogeneous, as they identify long-term relations between international food prices and domestic prices in more than half of European Union members.

All the above studies are careful to control for exchange rate variations, in light of the significant pass-through from depreciation to domestic inflation identified in the literature. In this regard, Takhtamanova (2010) and Mihaljek & Klau (2008) show evidence of a systematic pass-through decline, probably associated with low and stable inflation environments. In an application to Peru, Winkelried *et al.* (2012) find evidence of a statistically significant, although low, pass-through effect. In contrast, we find a relatively high pass-through effect, although the responses to exchange rate shocks are relatively less persistent; i.e., the impact from these shocks dissipates faster than that from other shocks (e.g., food price shocks). In fact, while the exchange rate is an important element in inflation dynamics, its contribution is found not to be the most relevant during inflation episodes, except for May 2015-June 2016 and September 2016-May 2017, where the exchange rate contributed around 55% of the departure of inflation from the center of the target band.

Bukeviciute, Dierx, Ilzkovitz, & Roty (2009), Davidson, Halunga, Lloyd, McCorriston, & Morgan (2016), and Rigobon (2010) show similar results. These studies examine the transmission channels from international commodity prices to retail prices across several countries; and report similar findings to those in this research, including, notably, a positive relationship between the weight of food and energy prices in the consumer basket and the impact of international food and energy price shocks. At the same time, they identify a positive inflation response to metal price shocks in advanced economies, which differs from the results in this study. However, it is a plausible result, considering the features of each individual economy; i.e., increased metal prices might be

[4] Baek & Koo (2010), Durevall, Loening, & Birru (2013), Lin & Xu (2019), and Chen, Zhu, & Li (2020) focus on data for a single economy (U.S., Ethiopia, China, and China, respectively. In contrast, Ferrucci, Jiménez-Rodrıguez, & Onorantea (2012) examines the eurozone; Sekine & Tsuruga (2018) assess 144 countries; and Cecchetti & Moessner (2008) study a number of advanced and emerging economies: Canada, Denmark, the eurozone, Japan, Norway, Sweden, Switzerland, UK, U.S., China, Chinese Taipei, Hong Kong SAR, Hungary, Indonesia, Korea, Mexico, Singapore, South Africa, and Thailand.

expected to have a greater impact on marginal production costs (and, therefore, on inflation) in an advanced net industrial metal importer than in a small, open metal exporter.

In turn, inflation dynamics in the face of external or domestic shocks can be influenced by the share of food items in the basic consumption basket and by the extent of the anchoring of inflation expectations. IMF (2011) and Furceri, Loungani, Simon, & Wachter (2016) explore the impact of international food price shocks on inflation in advanced and emerging economies. Both studies find that the pass-through from international food price increases to inflation is greater in emerging market economies, probably due to a higher share of food items in the consumption basket and a weaker anchoring of inflation expectations than in developed countries.

In practice, policy-makers are concerned with the pass-through effect of shocks, as it is typically interpreted as an elasticity and, therefore, can be used to make rule-of-thumb and readily available forecasts for the inflation response to sudden changes in the determinant variables. In contrast, the results of this study suggest that it is preferable to make "fast forecasts" using impulse responses instead of the pass-through effect, due to a significant inertia identified in domestic inflation, as shocks on determinant variables trigger increasing pass-through effects even when the impact from such shocks begins to dissipate.

The remainder of the document is organized as follows. Section 2 describes the econometric framework and the strategy for identifying structural shocks. Building on these results, Section 3 breaks down the estimation results into three metrics: impulse-response function (IRF), pass-through (PT) effect, and historical decomposition (HD) of structural shocks. Finally, Section 4 provides the conclusions of the study.

2 Methodology

We estimate a structural Bayesian VAR (BVAR) model with an external block comprising the indices for the following international commodity prices: energy (C^E), food (C^A), industrial metals (C^{MI}), and precious metals (C^{MP}). The external block is exogenous; i.e., changes in its variables affect those in the domestic block, but not vice versa.

The domestic block includes 12-month-ahead inflation expectations ($\Delta_{12}P^e$), the exchange rate (S), wholesale price indices (P^M), and the consumer price indices for food and energy (P^{FE}) and excluding those items (P^{EFE}).[5] All variables are represented as indices (2009=100), except for inflation expectations, expressed as 12-month log-differences.[6] The estimation sample starts in January 2001 and ends in December 2021.

Let $\mathbf{y}^* = [C^E,\ C^A,\ C^{MI},\ C^{MP}]'$ and $\mathbf{y} = [D_{12}P^e,\ S,\ P^M,\ P^{FE},\ P^{EFE}]'$ be the components of the external and domestic blocks in the system, respectively. Thus, $\mathbf{Y} = [\mathbf{y}',\ \mathbf{y}^{*\prime}]'$ is a 9×1 vector comprising all the variables in the system. Therefore, the structural BVAR can be expressed as follows:

$$t(\mathbf{Y}_t) = \mathbf{B}_0 + \sum_{\ell=1}^{p} \mathbf{B}_\ell t(\mathbf{Y}_{t-\ell}) + \mathbf{C}\mathbf{U}_t \text{ con } \mathbf{U}_t \overset{iid}{\sim} \mathcal{N}(\mathbf{0}, \mathbf{I}), \tag{2.1}$$

[5] The results for the consumer price index (P) are calculated outside the estimation using the following identity: $P = \omega P^{EFE} + (1-\omega)P^{FE}$ con $\omega = 0.56$.

[6] That is, $\Delta_{12}P^e_{t+12|t} = 100 \times \log \frac{P^e_{t+12|t}}{P_t}$, where $P^e_{t+12|t}$ is the expected consumer price index at moment t, 12 months ahead. This expected price is obtained from the BCRP's inflation expectations survey.

where $t(\cdot)$ is a function used to transform the data before entering them into the structural BVAR.[7]

As explained in Annex A, different specifications for $t(\cdot)$ imply different statistical properties; and, conditional on a limited number of lags, different results for the same data-generating process(DGP). Thus, it can be concluded that the choice of a transformation $t(\cdot)$ must result from a balance between the desirable statistical features and the economic relevance of the results. Along these lines, we used a large number of lags (i.e., $p = 13$), thereby improving the methodology's statistical performance. Additionally, the estimation is based on interannual differences, as this transformation yields results of greater economic relevance (presented in section 3). At the same time, as a transparency exercise, Annex C provides the estimations for the other transformations.

After disaggregating by blocks, the structural BVAR in (2.1) can be rewritten as:

$$\begin{bmatrix} t(\mathbf{y}_t) \\ t(\mathbf{y}_t^*) \end{bmatrix} = \begin{bmatrix} \mathbf{b}_0 \\ \mathbf{b}_0^* \end{bmatrix} + \sum_{\ell=1}^{p} \begin{bmatrix} \mathbf{b}_\ell & \mathbf{b}_{*\ell} \\ \mathbf{b}_\ell^* & \mathbf{b}_{*\ell}^* \end{bmatrix} \begin{bmatrix} t(\mathbf{y}_{t-\ell}) \\ t(\mathbf{y}_{t-\ell}^*) \end{bmatrix} + \begin{bmatrix} \mathbf{c} & \mathbf{c}_* \\ \mathbf{c}^* & \mathbf{c}_*^* \end{bmatrix} \begin{bmatrix} \mathbf{u}_t \\ \mathbf{u}_t^* \end{bmatrix}. \tag{2.2}$$

In a frequentist context, the exogeneity assumption for the external block implies imposing the following restriction in estimating (2.2):

$$\mathbf{b}_\ell^* = \mathbf{c}^* = \mathbf{0} \text{ for each } \ell \in \{1, ..., p\}. \tag{2.3}$$

Thus, as suggested by Canova (2005), restriction (2.3) directly introduces into (2.2) the impossibility for the external sector to respond to structural shocks originated in the domestic sector ($\mathbf{u}_t$). In contrast, under the Bayesian approach, the information in restriction (2.3) is introduced into the estimation via the prior for the coefficients in the case of $\mathbf{b}_\ell^*$. For its part, the restriction on $\mathbf{c}^*$ is actually part of the structural identification assumptions explained below.

Without the assumption of an exogenous external sector, the formulation for the prior in this document would be standard; i.e., we include simultaneously the **Minnesota**, **sum of coefficients**, and **arbitrary initial observation** priors.[8] Thus, introducing restriction (2.3) into the estimation implies extending the Minnesota prior so as to add a hyperparameter to control for the domestic sector's contribution to the external sector in the posterior distribution.

For extending the Minnesota prior, we define $b_{i,j}(\ell)$ as an element in row i and column j of $\mathbf{B}_\ell$ in (2.1). Thus, the prior for the said coefficient is assumed to be normally distributed with mean $\mathrm{E}b_{i,j}(\ell)$ and variance $\mathrm{var}(b_{i,j}(\ell))$, such that

$$\mathrm{E}b_{i,j}(\ell) = \begin{cases} \delta_i, & \text{if } i = j \text{ and } \ell = 1 \\ 0, & \text{otherwise} \end{cases} \quad \text{and } \mathrm{var}(b_{i,j}(\ell)) = \begin{cases} \frac{\pi_1^2 \pi_4^2}{\ell^2} \frac{\sigma_j^2}{\sigma_i^2} & \text{if } b_{i,j}(\ell) \in \mathbf{b}_\ell^* \text{ with } \ell > 0 \\ \frac{\pi_1^2}{\ell^2} \frac{\sigma_j^2}{\sigma_i^2} & \text{if } b_{i,j}(\ell) \notin \mathbf{b}_\ell^* \text{ with } \ell > 0 \\ \pi_5^2 \sigma_i & \text{if } \ell = 0 \end{cases}, \tag{2.4}$$

where ℓ and σ_i are the lags for the VAR matrix and the residual MCO for the i-th equation in the VAR. For their part, δ_i, π_1, and π_4 are the hyperparameters of the extended Minnesota prior distribution. These

[7] Specifically, the following transformations were used:

- Level: $t(x_t) = 100 \times \log x_t^{ae}$
- Annualized monthly log-difference: $t(x_t) = 1200 \times (\log x_t^{ae} - \log x_{t-1}^{ae})$
- Interannual log-difference: $t(x_t) = 100 \times (\log x_t^{ae} - \log x_{t-12}^{ae})$

where x_t^{ae} is the seasonally adjusted version of x_t, estimated using the TRAMO-SEATS filter.

[8] As proposed by Litterman (1986), Doan, Litterman, & Sims (1984), and Sims (1993), respectively.

hyperparamenters are intended to modulate the form of the prior distribution and calibrate the influence of the prior on the posterior distribution. Specifically,

- $\delta_i \in \{0, 1\}$ is the random walk hyperparameter. We assume that the variables in the VAR are random (i.e., non-stationary) walks if $\delta_i = 1$. In contrast, if $\delta_i = 0$, we assume the said variables to follow mean-reverting processes.

- $\pi_1,\ \pi_4,\ \pi_5 > 0$ are the global adjustment, external sector, and deterministic variable (intercept) hyperparameters. If $\pi_j \to 0$ ($\pi_j \to \infty$), the influence of the prior on the posterior distribution is strong (weak).

As π_4 affects only the coefficients in $\mathbf{b}^*_\ell$ and no element in $\mathbf{b}^*_\ell$ belongs in the main diagonal of $\mathbf{B}_1$, the posterior mean of $b_{i,j}(\ell) \in \mathbf{b}^*_\ell$ is approximately zero if π_4 is calibrated close enough to zero. Hyperparameters π_2 and π_3, absent in (2.4), are the adjustment hyperparameters associated with the sum of coefficients and arbitrary initial observation priors.

The prior for estimating the variance matrix in (2.1) is assumed to be inverted Wishart with $\alpha_0 = 11$ degrees of freedom and scale matrix $\mathbf{S}_0 = \text{diag}(\{\sigma_i^2\}_{i=1}^9)$. Thus, the joint prior for $\{\mathbf{B}_\ell\}_{\ell \geq 0}$ and $\mathbf{CC}'$ is known as the independent Normal-Wishart prior.

Hyperparameter π_4 is calibrated at 10^{-4}, as with this value the domestic sector effectively has no influence on the behavior of the international segment. For its part, π_5 if fixed at 100, which is equivalent to limiting the influence of the prior on the posterior mean of the intercept in the model. Table (1) shows that the δ_i hyperparameters are calibrated in line with the transformation of the variables in the VAR; i.e., if a price is entered into the structural BVAR as an index, then $\delta_i = 1$. In contrast, if a price is introduced as a log-difference, then $\delta_i = 0$.

Table 1. *Hyperparameter Calibration*

Hyperparameter	$t(\cdot)$: Estimation in	
	Levels	Annualized or interannual log-differences
Random walk (δ_i)	1	0
Adjustment: global (π_1)	0.13	0.14
Adjustment: sum of coefficients (π_2)	–	–
Adjustment: arbitrary initial observation (π_3)	0.1	0.1

The remaining hyperparameters (π_1, π_2 y π_3) are determined so as to maximize the marginal likelihood of the data. It should be noted that, with the selected prior, there is no analytical expression for the marginal likelihood of the data, as in Giannone, Lenza, & Primiceri (2015). Therefore, the likelihood is approximated numerically, as suggested by Chib (1995). The results in Table (1) indicate that it is optimal not to include the sum of coefficients prior and fix π_3 at 0.1 and π_1 at 0.13 for the VAR estimated using price indices and 0.14 for the VARs estimated using log-differences.

Identification

Follow the methodology proposed by Arias, Rubio-Ramírez, & Waggoner (2018), we combine zero and sign restrictions to identify the structural shocks in the system. We assume the external block to be recursive and use a Choleski identification scheme; i.e., as shown in the lower left panel of Table (2), variables in the external segment are ordered from least to most exogenous as follows:

$$C^{E} > C^{MI} > C^{MP} > C^{A}. \tag{2.5}$$

Specifically, we assume that shocks originated from energy prices have a contemporaneous impact on all other prices. Additionally, industrial metal price shocks have a contemporaneous impact on precious metal and food prices, but do not affect energy prices. Similarly, precious metal price shocks have a contemporaneous impact on food prices, but not on energy or industrial metal prices. Finally, structural shocks originated from food prices do not affect other commodity prices. It should be noted that we do not impose any restrictions on domestic variables' contemporaneous response to these shocks.

Appendix D presents an exercise intended to assess the changes in the results brought about by altering the ordering suggested by (2.5). Building on this assessment, it is possible to establish that the results in this study are robust to the ordering of the external variables. At the same time, there is room for improvement, as Cholesky identification excludes the possibility of potentially relevant simultaneity relations between prices (a pending issue our agenda for extending this line of research).

Table 2. *Contemporaneous Sign and Zero Restrictions*

Response from... \ Shock on...	P^{EFE}	P^{M}	S	$\Delta_{12}P^{e}$	P^{FE}	C^{F}	C^{PM}	C^{IM}	C^{E}
P^{EFE}		+	+	+					
P^{M}	+		+	+					
S									
$\Delta_{12}P^{e}$	+	+	+						
P^{FE}			+						
C^{F}	0	0	0	0	0				
C^{PM}	0	0	0	0	0	0			
C^{IM}	0	0	0	0	0	0	0		
C^{E}	0	0	0	0	0	0	0	0	

We assume that domestic variables have no contemporaneous impact on international variables (i.e., zeroes in the lower left quadrant of Table 2). As the estimation of the VAR reduced form includes an exogenous external block via the extension of the Minnesota prior described above, this absence of contemporaneous responses prevails across all periods.

Additionally, we imposed the least possible number of restrictions on the contemporaneous interactions between domestic variables, so as to ensure an agnostic identification procedure. The upper left quadrant of Table 2 presents these sign restrictions; and shows that no restrictions are imposed on the response to P^{FE} shocks.

Shocks on price expectations are assumed to have a positive contemporaneous impact on P^{EFE} and P^{M}. This restriction is justified by the price rigidities typically found in New Keynesian models. According to this theory, nominal rigidities are consistent with a Phillips curve where domestic inflation anticipates the future inflation sequence.[9] In fact, it suggests a simultaneity between observed and expected prices, which provides further justification for restricting positive inflation expectation responses to shocks originated from P^{EFE} and P^{M}.

[9] See, for example, the canonical New Keynesian models described in Woodford (2011), Galí (2015), and Walsh (2017)

Additionally, we assume a positive simultaneity between P^M and P^{EFE}, which materializes into a positive restriction on both variables' response to shocks originated from P^{EFE} and P^M.

3 Results

We calculate three metrics, typically used for analyzing multivariate time series, to assess the results of the estimations: impulse response function (IRF), pass-through (PT) effect, and historical decomposition (HD). The analysis focuses on the response of domestic inflation and its components to shocks on metal and non-metal prices, the exchange rate, and inflation expectations.

3.1 Impulse-Response Function

The IRF measures the dynamics of the reaction of a given variable (variable i) to a structural shock on another variable (variable j) occurred τ periods ago. Formally, the IRF is calculated as:

$$IRF_{ij}(\tau) = \frac{\partial y_{i,t}}{\partial \epsilon_{j,t-\tau}}. \tag{3.1}$$

Thus, a (one-standard deviation) shock originated from variable j occurred τ periods ago generates, at present, a $IRF_{ij}(\tau)$-unit increase in variable i.

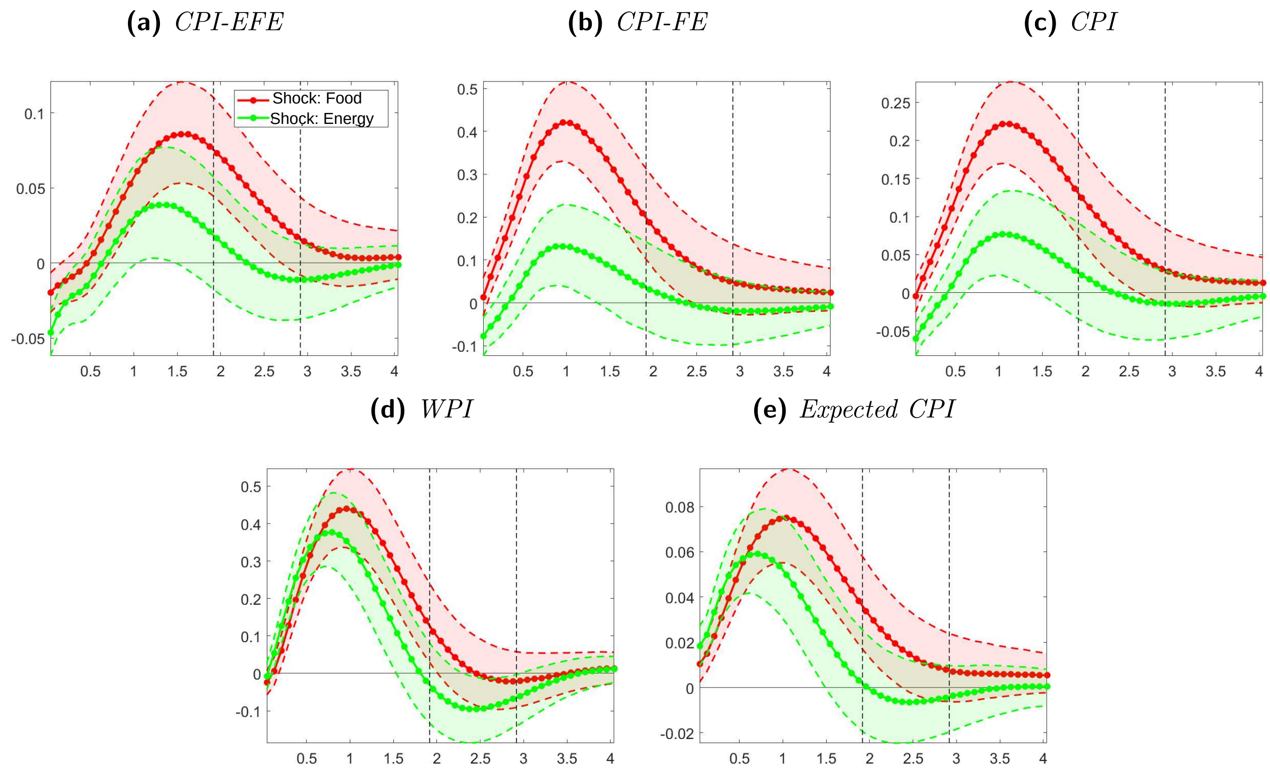
The responses are presented as interannual variations in P^{EFE} (CPI-EFE), P^{FE} (CPI-FE), P^M (WPI), P (CPI), and $\Delta_{12}P^e$ (expected inflation) caused by shocks on international non-metal prices (Figure 3), the exchange rate, and expected inflation (Figure 5). Additionally, Table 3 shows the maximum responses and the number of periods to reach them according to the IRFs. Finally, with the purpose of making rule-of-thumb and readily available forecasts, Table 4 shows the standardized response of the multiple measures of domestic inflation one-two years after the occurrence of a shock.

International Non-Metal Prices

Figure 3 shows the responses to positive impulses from international food (red area) and energy (green area) price shocks. The IRFs suggest that these shocks are inflationary in both the short and medium run, as such commodities are important inputs to domestic production and take a considerable share of the CPI basket. Therefore, an increase in their prices exacerbates marginal production costs, in turn affecting domestic inflation (directly and indirectly) via the response in inflation expectations. The same figure shows that both kinds of shocks trigger qualitatively similar responses, although food price shocks seem to have longer and more protracted effects on all measures of domestic inflation.

All measures of inflation are mean-reverting (after 5 semesters at most); but persistence across types of shocks is found to be considerably heterogeneous. In general, food price shocks seem to cause greater and more persistent responses.

Figure 3. *Interannual Inflation Responses to Non-Metal Price Shocks*



(a) *CPI-EFE* **(b)** *CPI-FE* **(c)** *CPI* **(d)** *WPI* **(e)** *Expected CPI*

Note. IRFs are calculated for one-standard deviation shocks on food (red) and energy (green) prices. The areas correspond to a credible interval of 68%.

CPI-EFE inflation shows the maximum persistence with the least impact (Figure 3a); i.e., between 16-18 months after the shock, and not exceeding 0.1 p.p. and 0.05 p.p. in CPI-EFE variation for food and energy shocks, respectively (Table 3). This result is not surprising, as the CPI-EFE basket excludes the most volatile prices and, conceptually, considers only those prices showing the most rigid formation processes. On the other end, WPI and CPI-FE variations (Figures 3d and 3b) show the greatest responses within the domestic block, peaking 9-11 months after the shock (Table 3), reflecting these industries' ability to adjust their production costs faster (as their prices show the least rigid formation processes). Thus, following an international food price shock, the maximum impacts on IMP and CPI-FE interannual variations are 0.44 p.p. and 0.42 p.p., respectively. A shock on the international energy price interannual variation triggers a maximum impact of 0.38 p.p. on WPI variation, but a significantly lower one (0,13 p.p.) on CPI-FE variation (Table 3).

The behavior of inflation expectations (Figure 3e) results from the feedback dynamics in the measures of domestic inflation. Higher CPI-FE and WPI inflation induces future increases in CPI inflation, in turn affecting the formation of market participants' inflation expectations. We find that non-metal price shocks trigger the least persistent responses among domestic block variables, which rapidly converge back towards their mean values. Additionally, the maximum impact on inflation expectations occurs 8 and 12 months after the occurrence of international energy or food price shocks, respectively (Table 3).

The CPI inflation response can be defined as the weighted average of CPI-EFE and CPI-FE interannual variation responses, in turn influenced by the response of wholesale prices and inflation expectations. Table 3 shows that CPI inflation takes around 13 months to peak at 0.2 p.p. in response to an international food price shock, compared with 0.1 p.p. 12 months after an energy price shock.

The information in Table 4 can be used to make "ad-hoc" forecasts on the measures of domestic inflation for a single one-standard deviation shock (holding all other variables constant), which can be easily re-scaled for the actual size of a shock.

Thus, policymakers may find it useful to predict inflation increases of 0.083% and 0042% in the first and second year, respectively, in response to a 1% increase in food prices; i.e., the inflation response is expected to be strong in the first quarters and dissipate thereafter. In line with this result, the model predicts the CPI-FE interannual variation to increase 0.157% in the first year and decline to less than half that change, to 0.062%, by the end of the second year. Only the CPI-EFE shows a slight increase, probably associated with the persistence identified in this variable; i.e., CPI-EFE inflation goes from 0,023% to 0,026% between the first and second years.

The IRF results in the case of an energy price shock are quantitatively lower, as its standard deviation is three times greater than that of food price shocks (Table 4). Similarly, the model predicts inflation to increase 0.007% after one year for each 1% increase in energy prices. Specifically, wholesale prices increase 0.031% and 0.163% in the first year in response to energy and food price shocks, respectively.

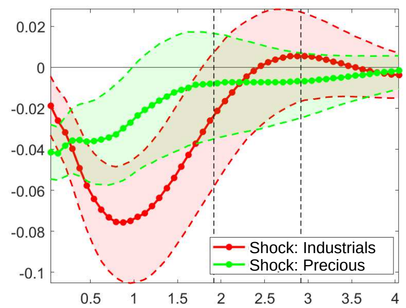
International Metal Prices

Figure 4 shows the IRFs for the the measures of inflation in response to industrial (red) and precious (green) metal price shocks. These are qualitatively opposed to responses to non-metal price shocks; i.e., the IRFs are generally negative and, in some cases, non-significant (see responses to precious metal price shocks in 4b, 4d, and 4e).

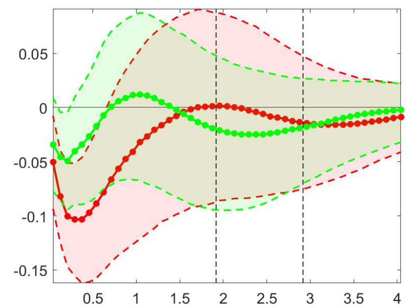
In general, increases in these prices favor mining commodity exports; i.e., these shocks have positive effects on domestic economic and financial conditions. Specifically, increased mining exports brought about by improved international prices induce an exchange rate appreciation (in turn caused by greater foreign exchange inflows) and a reduction in inflation expectations, both of which translate into lower inflation pressures.

Figure 4. *Interannual Inflation Responses to Metal Price Shocks*

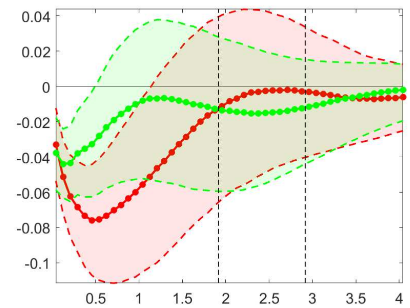
(a) *CPI-EFE*



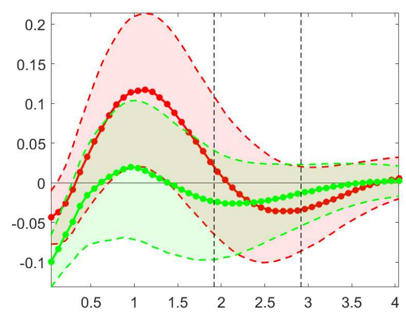
(b) *CPI-FE*



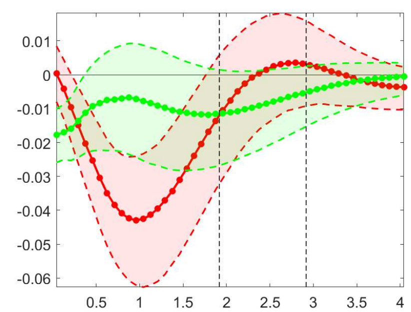
(c) *CPI*



(d) *WPI*



(e) *Expected CPI*



Note. IRFs are calculated for one-standard deviation shocks on industrial (red) and precious (green) metal prices. The areas correspond to a credible interval of 68%.

Additionally, we find that the reversion to the mean starts rapidly in the case of precious metals; i.e., Table 3 shows that all measures of inflation reach a maximum contraction between the initial period and the second month after a precious metal price shock. In contrast, industrial metal price shocks trigger a larger contraction with a slower reversion to the mean (around two semesters); e.g., CPI-EFE and CPI-FE inflation rates fall to a maximum of 0.076% and 0.103% on the tenth and third months after the shock, respectively. When aggregating both results, CPI inflation drops to 0.076% (see 4c) and starts reverting to the mean after the first year.

This differentiated response is likely associated with the predominant share of industrial metals in Peru's commodity exports; i.e., increases in industrial metal prices have a greater impact on the dollar value of mining exports.

The response of WPI inflation is somewhat surprising, as its behavior is opposite to that of other measures of domestic inflation (see 4d). At the same time, it is worth noting the important and persistent response of inflation expectations to this kind of shock (see 4e). Inflation expectations peak after 11 months and revert to the mean on the third quarter. This response may be associated with a downward adjustment of market participants' inflation forecasts in view of more favorable external conditions.

Finally, Table 4 shows the quantification of the standardized response. The most outstanding result is the reduction of inflation to an annual 0.009% in response to a 1% increase in industrial metal prices. In year 2 the response becomes non-significant. Similarly, the model predicts a 0.011% fall in CPI-EFE inflation and a 0.018% increase in WPI inflation. It should be noted that, in both cases, the standardized response is predicted to revert to zero by year 2. In the case of precious metals, the standardized responses are not significantly different from

0% over the periods shown in Table 4.

Inflation Expectations and Exchange Rate

Finally, Figure 5 presents some results for domestic events. We simulate the response to exchange rate depreciation (red) and inflation expectations (green) shocks. At this point, it is important to keep in mind that the system does not include economic activity or policy response variables. Therefore, it is possible that innovations identified as "structural" do not separate supply and demand shocks accurately. However, the exercise remains relevant, as it describes the average responses to unpredictable movements in the exchange rate and inflation expectations.[10]

Figure 5 shows that responses to an exchange rate depreciation are systematically positive and relatively persistent; e.g., Table 3 shows that CPI-EFE variation peaks at 0.082 p.p. after 10 periods and reverts to the mean after 6 semesters (Figure 5a). In contrast, CPI-FE variation responds rapidly and peaks during the initial period; i.e., total inflation also peaks in period zero. Figures 5b and 5c show that the IRFs revert to the mean completely after 36 periods. In this line, CPI-FE variation reaches a 0.281-p.p. increase.[11]

Additionally, the IRFs show very heterogeneous results for the expectations shock. In this case, only CPI-EFE inflation seems to experience a significant increase in the initial periods, peaking at the eighth month and reverting to the mean around period 12 (Table 3). In general, 5 shows that expectations trigger initial increases only in WPI and EFE inflation, while total inflation does not show significant changes.

Although there is room for improving the identification process (by including activity indicators), the reduced response to inflation expectations shocks is somewhat surprising. If this result were to be confirmed, it would provide evidence that market participants form their expectations based on the information in the variables of the system carrying a largely irrelevant speculative component.

Table 4 shows quantitatively the predictions for the standardized responses to both shocks. The most outstanding results are the responses to an exchange rate shock, which are significant for years 1 and 2. In sum, inflation is forecast to increase by 0.190% in year 1 and 0.110% in year 2 in response to a 1% exchange rate depreciation. This gradual fall in inflation is accompanied by lower EFE and FE increases in year 2. For their part, the CPI-FE and CPI-EFE inflation rates are forecast to increase by 0.280% and 0.180%, and by 0.116% and 0.053%, respectively, in years 1 and 2. Similarly, the increase in expectations concentrates in year 1 (0.056%) but drops to almost half that figure after 12 months (0.029%).

In the case of an expectations shock, we find that only CPI-EFE inflation experiences a 1.477% increase in year 1. The remaining inflation variables do not show significant changes over the horizon presented in the table.

3.2 Pass-Through Effect

The PT is a relative average measure of the sensitivity or response over time of a variable of interest (variable i) triggered by shocks originated from another variable (variable j). Specifically,

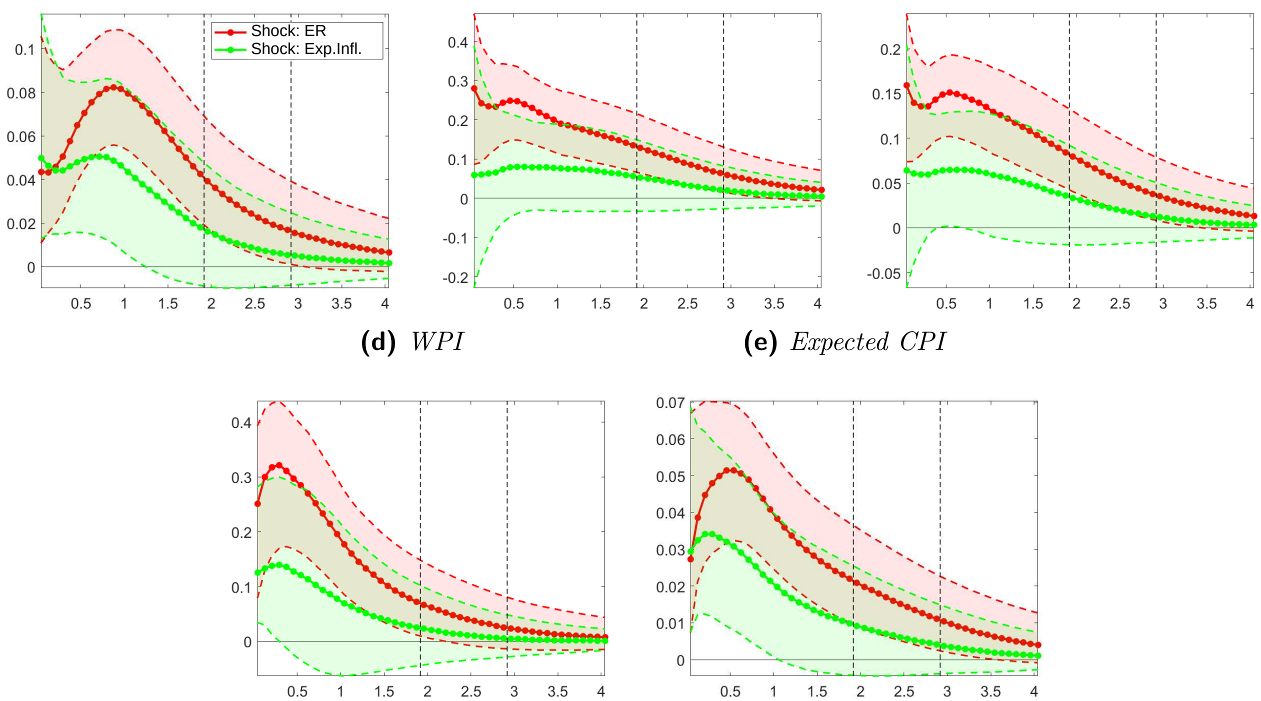
$$PT_{ij}(t) = \frac{\sum_{\tau=1}^{t} IRF_{ij}(\tau)}{\sum_{\tau=1}^{t} IRF_{jj}(\tau)}.$$

[10] As mentioned above, including economic activity and policy response variables implies the need to explore nonlinear relations, in light of the considerable fluctuations in such variables since the pandemic outbreak.

[11] This effect corresponds to the imported inflation component affecting both CPI-EFE and CPI-FE, thereby increasing the cost of the basic basket via a higher exchange rate for local producers and consumers.

Figure 5. *Interannual Inflation Responses to Exchange Rate and Expectations Shocks*

(a) *CPI-EFE* **(b)** *CPI-FE* **(c)** *CPI* **(d)** *WPI* **(e)** *Expected CPI*



Note. IRFs are calculated for one-standard deviation shocks on the exchange rate (red) and inflation expectations (green). The areas correspond to a credible interval of 68%.

Table 3. *Maximum Responses to Structural Shocks*

Shock to ...			Response of ... P^{exp}	P^W	P^{FE}	P^{EFE}	P
	C^E	Max.	0.059	0.377	0.132	0.039	0.077
		Month	8	9	11	16	12
	C^F	Max.	0.075	0.439	0.421	0.086	0.222
		Month	12	11	11	18	13
	C^{IM}	Max.	-0.043	0.117	-0.103	-0.076	-0.076
		Month	11	13	3	10	5
	C^{PM}	Max.	-0.018	-0.100	-0.049	-0.042	-0.044
		Month	0	0	2	1	1
	S	Max.	0.051	0.321	0.281	0.082	0.159
		Month	6	3	0	10	0
	P^{exp}	Max.	0.034	0.139	0.081	0.051	0.065
		Month	2	3	6	8	7

Note. P^e: Expected Prices; P^W: Wholesale Prices; P^{FE}: CPI Food & Energy; P^{EFE}: CPI Ex Food & Energy; P: CPI, S: Exchange Rate; C^E: Energy Prices; C^F: Food Prices; C^{IM}: Industrial Metal Prices; and C^{PM}: Precious Metal Prices. IRFs computed for one-standard deviation shocks.

Thus, a shock on variable j sets in motion an average dynamics in variable i equivalent to the $PT_{ij}(t)$ of the average response in variable j after t periods. It is important to note that this definition implies that PT increases do not necessarily involve greater responses from in the variables of interest.[12]

Table 5 presents the PTs calculated for the domestic variables. In particular, the increases in the PTs between years 1 and 2 stand out. Specifically, the PT from food commodities to inflation increased from 0.053% to 0.128%. Similarly, the PT in CPI-FE and WPI rises from 0.112% to 0.239%, and from 0.112% to 0.225%, respectively. That is, in all cases the cumulative shock grows between years 1 and 2, reflecting that inflation would likely remain in positive territory after 5 semesters.

In order to validate this, Table 4 presents the standardized IRFs for a 1% increase in the variables. Thus, we verify that, although the CPI response to a food price shock declines from 0.083% to 0.042% between years 1 and 2, it remains significantly positive; i.e., given the persistence of domestic variables, although the inflation response to shocks lingers into year 2, it peaks at an earlier stage.

The pass-through from international food prices to CPI-FE inflation goes from 0.112% in year 1 to 0.225% in year 2, reflecting the considerable reliance of the FE basket on imported goods. Additionally, the PT is 0.006% and 0.039% for CPI-EFE inflation; and 0.021% and 0.044% for expectations, evidencing alternative channels through which non-metal commodity prices also affect prices in other markets and bear on market participants' inflation forecasts.

It is worth pointing out that metal price shocks have significant effects, mainly on CPI-EFE inflation and expectations (Table 5). At the same time, CPI-FE inflation diminishes in response to industrial metal price shocks only during year 1, but is not affected by precious metal prices shocks. Additionally, WPI inflation does

[12] Annex B provides an example to illustrate this point.

Table 4. *Standardized IRF*

		P^{exp}	P^{W}	P^{FE}	P^{EFE}	P
C^{E}	1 year	0.005*	0.031*	0.012*	0.003*	0.007*
		(0.003, 0.007)	(0.020, 0.042)	(0.003, 0.021)	(0.000, 0.006)	(0.002, 0.012)
	2 years	0.000	−0.006	0.002	0.001	0.002
		(−0.002, 0.002)	(−0.015, 0.004)	(−0.007, 0.012)	(−0.002, 0.005)	(−0.004, 0.008)
C^{F}	1 year	0.028*	0.163*	0.157*	0.023*	0.083*
		(0.021, 0.036)	(0.123, 0.204)	(0.122, 0.193)	(0.011, 0.034)	(0.063, 0.103)
	2 years	0.011*	0.032	0.062*	0.026*	0.042*
		(0.004, 0.019)	(−0.004, 0.073)	(0.026, 0.104)	(0.014, 0.038)	(0.021, 0.066)
C^{IM}	1 year	−0.007*	0.018*	−0.005	−0.011*	−0.009*
		(−0.010, −0.004)	(0.003, 0.033)	(−0.019, 0.008)	(−0.016, −0.007)	(−0.016, −0.001)
	2 years	−0.001	0.001	0.000	−0.003	−0.001
		(−0.004, 0.001)	(−0.012, 0.014)	(−0.013, 0.013)	(−0.008, 0.002)	(−0.009, 0.007)
C^{PM}	1 year	−0.002	0.004	0.002	−0.005	−0.002
		(−0.005, 0.002)	(−0.015, 0.022)	(−0.014, 0.018)	(−0.011, 0.001)	(−0.011, 0.007)
	2 years	−0.002	−0.005	−0.005	−0.002	−0.003
		(−0.005, 0.000)	(−0.020, 0.007)	(−0.020, 0.009)	(−0.007, 0.003)	(−0.012, 0.005)
S	1 year	0.056*	0.259*	0.280*	0.116*	0.190*
		(0.035, 0.080)	(0.125, 0.403)	(0.163, 0.402)	(0.078, 0.157)	(0.120, 0.262)
	2 years	0.029*	0.090*	0.180*	0.053*	0.110*
		(0.012, 0.051)	(0.007, 0.201)	(0.087, 0.300)	(0.023, 0.094)	(0.054, 0.183)
P^{exp}	1 year	0.671	2.349	2.587	1.477*	2.002
		(0.178, 2.763)	(−2.153, 7.035)	(−1.159, 6.440)	(0.178, 2.763)	(−0.352, 4.310)
	2 years	0.294	0.703	1.724	0.501	1.057
		(−0.325, 1.479)	(−1.403, 3.166)	(−1.122, 4.790)	(−0.325, 1.479)	(−0.656, 2.926)

Note. P^{exp}: Expected Prices; P^{W}: Wholesale Prices; P: CPI; P^{EFE}: CPI Ex Food & Energy; P^{FE}: CPI Food & Energy; S: Exchange Rate; C^{E}: Energy Prices; C^{F}: Food Prices; C^{IM}: Industrial Metal Prices; and C^{PM}: Precious Metal Prices. IRFs standardized in terms of standard deviations to measure the response to a 1% increase.

Table 5. *Pass-Through Effect*

		P^{exp}	P^{W}	P^{FE}	P^{EFE}	P
C^{E}	1 year	0.006*	0.035*	0.007	−0.001	0.003
		(0.004, 0.008)	(0.026, 0.045)	(−0.001, 0.015)	(−0.004, 0.002)	(−0.002, 0.007)
	2 years	0.009*	0.051*	0.017*	0.003	0.009
		(0.005, 0.014)	(0.029, 0.074)	(−0.003, 0.038)	(−0.004, 0.010)	(−0.002, 0.022)
C^{F}	1 year	0.021*	0.112*	0.112*	0.006	0.053*
		(0.016, 0.026)	(0.085, 0.137)	(0.088, 0.136)	(−0.002, 0.014)	(0.040, 0.066)
	2 years	0.044*	0.225*	0.239*	0.039*	0.128*
		(0.032, 0.057)	(0.163, 0.286)	(0.186, 0.298)	(0.019, 0.059)	(0.095, 0.162)
C^{IM}	1 year	−0.006*	0.010	−0.016*	−0.012*	−0.014*
		(−0.009, −0.003)	(−0.004, 0.023)	(−0.028, −0.004)	(−0.016, −0.008)	(−0.020, −0.007)
	2 years	−0.013*	0.026	−0.020	−0.025*	−0.023*
		(−0.019, −0.006)	(−0.006, 0.060)	(−0.049, 0.010)	(−0.036, −0.014)	(−0.040, −0.005)
C^{PM}	1 year	−0.004	−0.008	−0.006	−0.013*	−0.010
		(−0.008, 0.000)	(−0.031, 0.014)	(−0.026, 0.014)	(−0.020, −0.007)	(−0.021, 0.001)
	2 years	−0.007	−0.010	−0.009	−0.017*	−0.013
		(−0.016, 0.001)	(−0.054, 0.032)	(−0.049, 0.031)	(−0.030, −0.003)	(−0.036, 0.010)
S	1 year	0.089*	0.544*	0.466*	0.142*	0.290*
		(0.039, 0.260)	(0.323, 1.155)	(0.222, 1.245)	(0.078, 0.351)	(0.158, 0.743)
	2 years	0.119*	0.655*	0.660*	0.221*	0.418*
		(0.042, 0.326)	(0.355, 1.379)	(0.303, 1.660)	(0.112, 0.515)	(0.212, 1.023)
P^{exp}	1 year	1.000*	3.836	2.864	1.420*	2.208*
		(1.000, 1.000)	(−0.793, 9.755)	(−1.428, 6.830)	(0.365, 4.166)	(0.218, 4.412)
	2 years	1.000*	3.982	3.726	1.613*	2.649*
		(1.000, 1.000)	(−1.010, 8.617)	(−0.229, 7.089)	(0.439, 3.559)	(0.428, 4.689)

Note. P^{exp}: Expected Prices; P^{W}: Wholesale Prices, P: CPI; P^{EFE}: CPI Ex Food & Energy; P^{FE}: CPI Food & Energy; S: Exchange Rate; C^{E}: Energy Prices; C^{F}: Food Prices; C^{IM}: Industrial Metal Prices; and C^{PM}: Precious Metal Prices.

not respond significantly to any shocks, evidencing the channel through which metal price shocks translate into domestic prices. The standardized response shows that an industrial metal price shock triggers 0,007% and 0,011% reductions in expectations and CPI-EFE inflation, respectively, during year 1. In contrast, the response is no longer significant in year 2. A precious metal price shock sets similar developments in motion, except that inflation returns to its previous levels and the shock no longer triggers significant effects after one year.

In particular, an increase in metal commodity prices seems to affect mainly CPI-EFE inflation and inflation expectations. The adjustment in CPI-EFE inflation might be directly associated with the recoil in expectations promoted by better external conditions and a more favorable exchange rate for local prices. Finally, given the reduced FE response, total inflation captures the weighted effect from the shock, thereby converging more rapidly than CPI-EFE inflation, but later than CPI-FE inflation. Thus, Table (5) shows that the maximum contractions in CPI-EFE inflation and expectations are -0,08% and -0,04%, respectively. Both peaks occur 10 and 11 periods, respectively, after the impulse from industrial metals. For its part, inflation bottoms at -0.08, five periods before CPI-EFE inflation, due to a strong initial fall in CPI-FE inflation. Finally, the impact from a precious metal price shock on inflation measures occurs during the initial months.

Thus, Table (5) shows that a 1% increase in industrial metal prices triggers cumulative 0.009% and 0.001% falls in inflation in years 1 and 2, respectively, mainly reflecting the effect on CPI-EFE inflation and inflation expectations. For their part, precious metal price shocks have a significant impact only on CPI-EFE inflation, where the pass-through is -0,005 in year 1 and -0,002 in year 2.

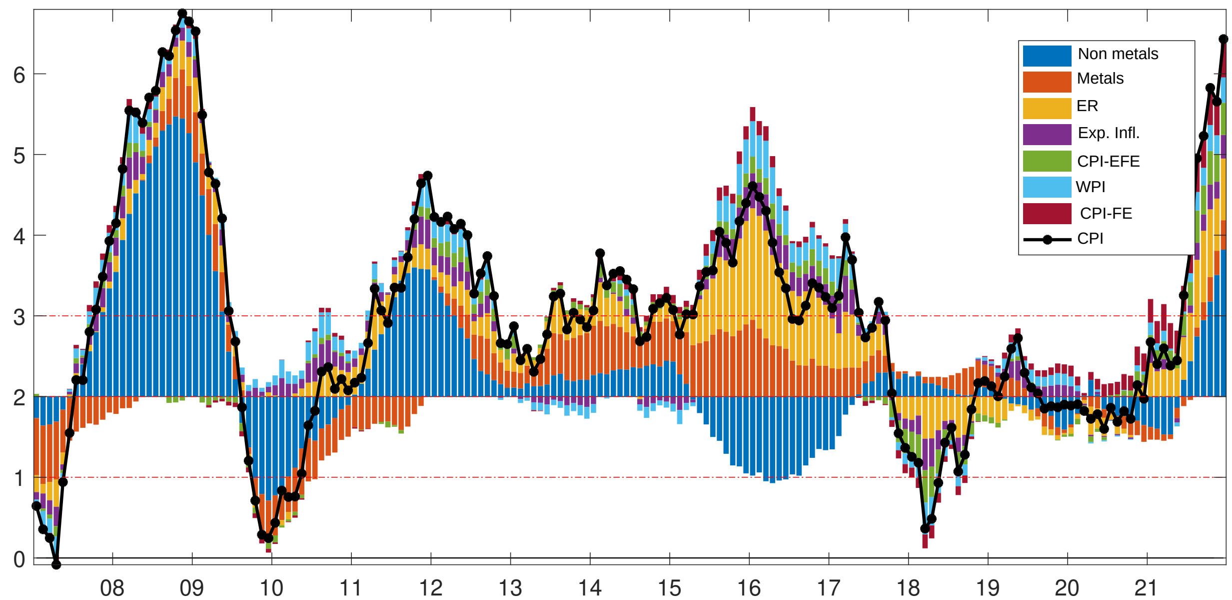
Table 5 also shows the response to exchange rate and expectations shocks. As mentioned above, a 1% expectations shock elicits a 1.477% response during year 1 only in CPI-EFE inflation, while the remaining measures do not experience significant changes, since the direct pass-through from an increase in expectations to CPI-EFE inflation declines as the monetary authority reacts to the surge in inflation. In contrast, an exchange rate shock does trigger persistent effects on inflation; e.g., the response of total inflation to a 1% depreciation in year 1 is an increase of up to 0.190%, which declines to 0.110% in year 2. As expected, an exchange rate shock affects all measures of inflation, as well as inflation expectations (in response to the increase in CPI-EFE and total inflation).

3.3 Historical Decomposition

Figure 6 presents the historical contribution of each variable in the model to CPI inflation. Especially, external factors show a significant contribution, notably non-metal commodity prices, during 2007-2015. This situation changes starting the second half of 2015, as the contribution of metal commodity prices and the exchange rate (the domestic factor) begin to predominate in local inflation dynamics.

This can be verified in Table 6, which shows the contribution of each shock during the episodes where inflation departed significantly from the target band. During the 2007-2009 inflation episode in the context of the Global Financial Crisis (GFC), the deviation from the inflation target was 3.17 p.p. on average, of which non-metal commodities explain 2.26 p.p. (i.e., close to 71.5%). Among domestic factors, the exchange rate contributed 0.24 p.p. to the increase in inflation, although it explained just 7.6% of the deviation from the target.

Figure 6. *Historical Decomposition of Interannual CPI Inflation (contributionbs centered on the inflation target)*



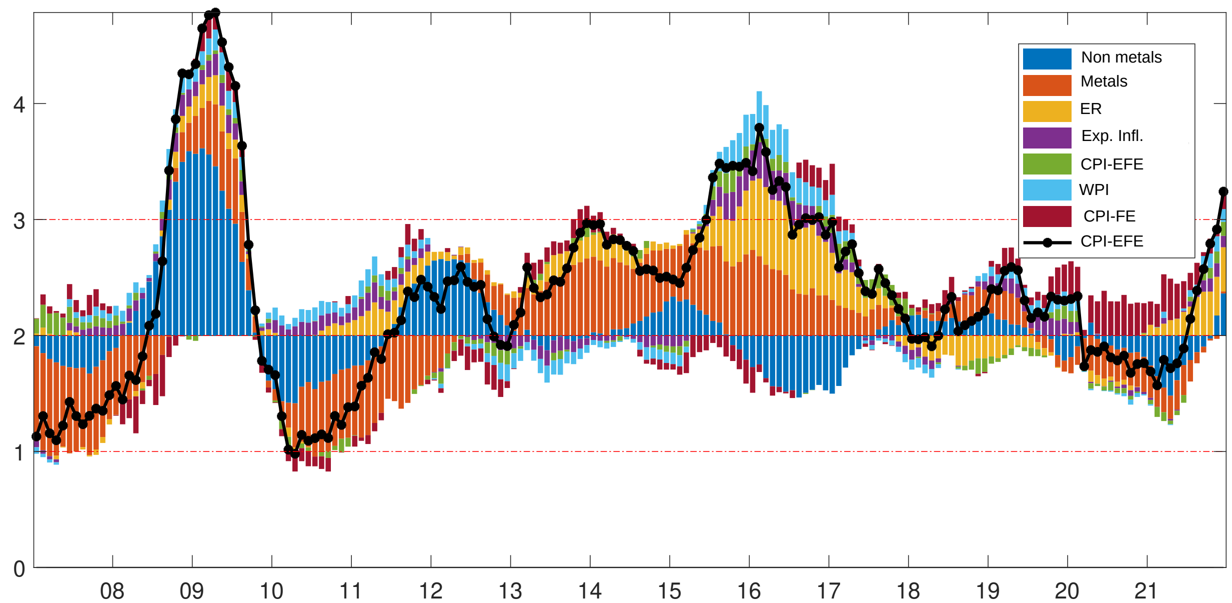
Global deceleration and a decline in non-metal commodity prices led to an unwinding of inflation pressures in 2010 (Figure 6). In that year, metal and non-metal commodities were the main determinants of inflation, but with negative contributions, which reverted since July 2011. A new persistent inflation process took place in July 2011-October 2012, with an average deviation of 1.91 p.p., of which non-metal prices explained 54.4% (up to 1.04 p.p.). A further persistent inflation process occurred in July 2014, characterized by the importance of non-metal commodity prices. In this episode, metal and non-metal commodity prices contributed 0.54 p.p. (37.7%) and 0.31 p.p. (21.8%) to the inflation deviation, respectively.

In the following inflation episodes, the contribution of non-metal commodities declines considerably; and domestic factors (particularly the exchange rate) play a greater role in determining inflation. Table (6) shows that the exchange rate triples its contribution to inflation, from 0.31 p.p. in the 2014 episode, to 1.01 p.p, 0.69 p.p, and 0.73 p.p. in the 2015-2016, 2016-2017, and 2021 episodes, respectively. The contribution of metal prices to inflation also increases, from 0.54 p.p. in the 2014 episode, to 0.76 p.p. in the 2015-2016 episode; but declines in the last two episodes (0.37 p.p and 0.16 p.p. in the 2016-2017 and 2021 episodes, respectively).

Inflation pressures (both external and domestic) receded under the pandemic and inflation remained within around the target, which enabled the Central Reserve Bank of Peru (BCRP) to maintain an expansionary stance in the most critical moments of the crisis. However, starting the second half of 2021, external inflation pressures surged (mainly from non-metal commodity prices). In this context, the average departure from the target was 3.02 p.p. in June-December 2021, of which 0.98 p.p., 0.73 p.p., and 0.40 p.p. can be attributed to the increase in non-metal prices, world depreciation, and shocks on CPI-FE, respectively. This situation might continue as long as pandemic-related disruptions in the global supply chain persist.

Similarly, Figure 7 shows the historical decomposition of CPI-EFE inflation. As in the case of total inflation, there were several episodes where CPI-EFE inflation departed from the target band, although it experienced less pronounced peaks and lower deviations from the target band (as it excludes the most volatile elements of inflation). At the same time, domestic factors contributed to a greater extent, although external factors continued to be the most relevant.

Figure 7. *Historical Decomposition of Interannual CPI-EFE Inflation (contributions centered on the inflation target)*



For its part, the historical decomposition of CPI-FE inflation (Figure 8) shows greater volatility and a higher predominance of external factors; e.g., during the GFC, the increase in international prices largely explain the deviation of inflation from the target band. Similarly, in the most recent episode, international prices and the exchange rate contributed more than 50% of the increase in CPI-FE inflation.

Figure 8. *Historical Decomposition of Interannual CPI-FE Inflation (contriburions centered on the inflation target)*

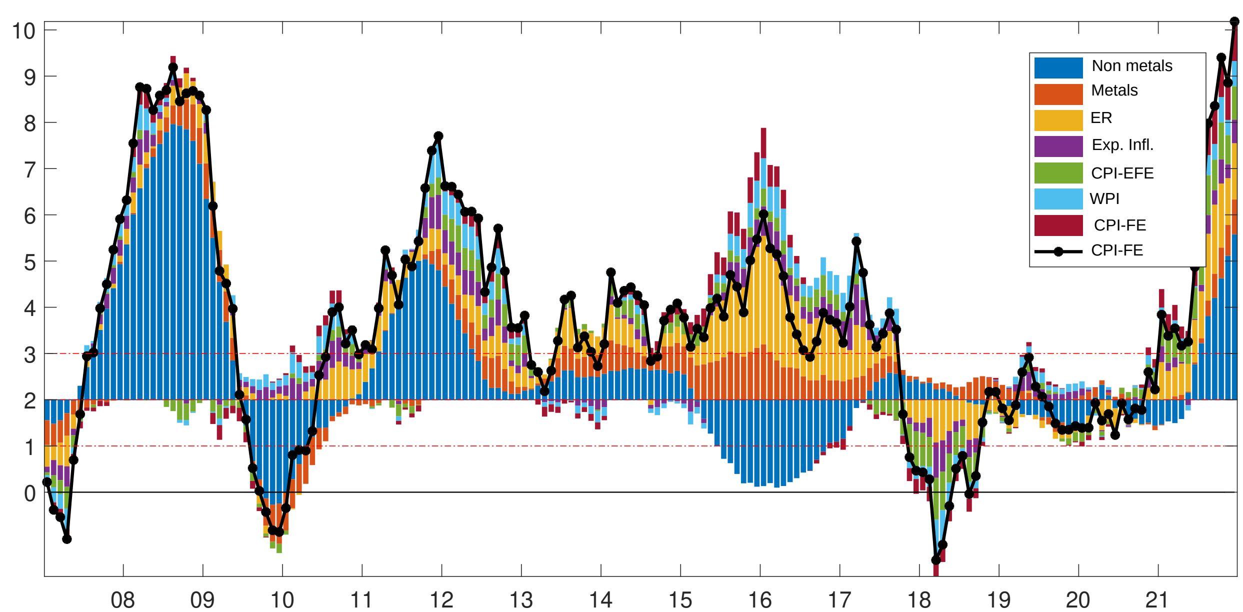


Table 6. *Episodes of Inflation Above 3% and Longer than 6 Months*

	Prices		**Exp.**	**TC**	**EFE**	**FE**	**WPI**	**Deviation from target band**
	Metal	Non-Metal						
	(A)	(B)	(C)	(D)	(E)	(F)	(G)	(A+B+C+D+E+F+G)
Oct.07 - Jun.09	0,20	2,26	0,19	0,24	0,03	0,06	0,18	3,17
Jul.11 - Oct.12	0,07	1,04	0,20	0,24	0,12	0,06	0,19	1,91
Jan.14 - Jul.14	0,54	0,31	0,03	0,31	0,13	0,10	0,02	1,44
May.15 - Jun.16	0,76	-0,79	0,32	1,01	0,17	0,14	0,32	1,92
Sep.16 - May.17	0,37	-0,49	0,28	0,69	0,16	0,04	0,29	1,35
Jun.21 - Dic.21	0,16	0,98	0,19	0,73	0,35	0,40	0,21	3,02
December 2021	0,36	1,82	0,29	0,76	0,40	0,48	0,31	4,43

Note. The **deviation from the target band** is the average 12-month inflation in each period minus 2%. The left-hand panel shows the average contributions in each period.

3.4 Counterfactual Exercise on Recent Inflation Dynamics

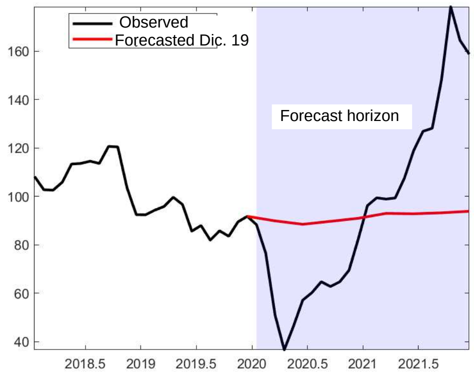
An alternative way of assessing the contribution of recent external sector dynamics to domestic inflation is to calculate the inflation that would have materialized if commodity prices had held their expected pre-pandemic values (as of December 2019); i.e., these calculations exclude the impact of pandemic-related disruptions in the global supply chain.

The counterfactual scenario considers the pre-pandemic international price forecasts for 2020 and 2021, drawn from the *Energy and Metals Consensus Forecast* (December 2019) and World Bank Group (2019) (for food prices).[13] Forecasts for aggregate indices per category are built using the weights suggested in the IMF guidelines, which in turn consider the volume of global commodity trade. In the case of food commodities, it should be noted that, although the series used in the estimation was drawn from FAO, the agriculture index built using the IMF weights generate a similar dynamics.

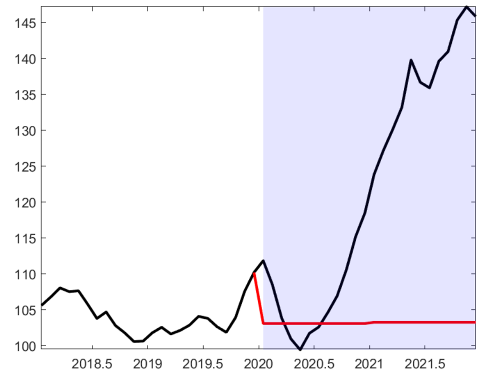
[13] The figures in the *Energy and Metals Consensus Forecast* are calculated by *Consensus Economics*, available (with restrictions) at https://www.consensuseconomics.com/publications/energy-and-metals-consensus-forecasts.

Figure 9. *Counterfactual International Price Forecasts*

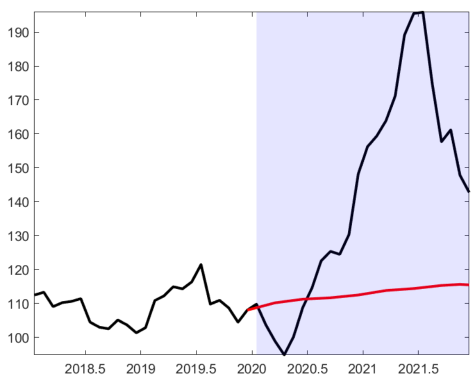
(a) *Energy*



(b) *Food*



(c) *Industrial Metals*



(d) *Precious Metals*

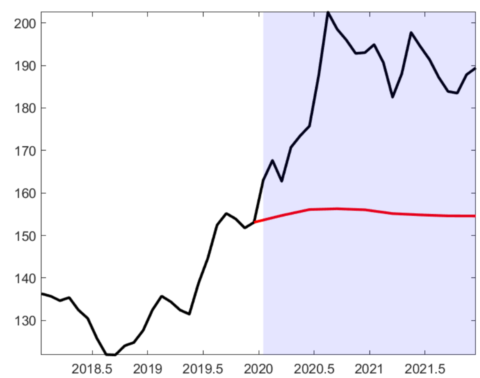
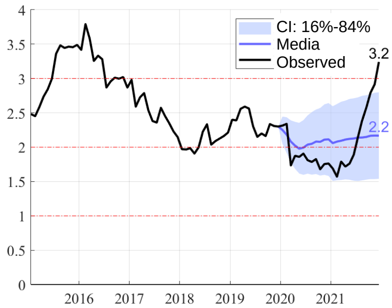


Figure 9 shows the commodity index forecasts in the counterfactual scenario. In general, the forecasts (issued before the possibility of a pandemic was even considered) are stable around the pre-pandemic observable trends (red lines), with slight increases in certain cases. The actual values turned out to be markedly different. Energy, food, and industrial metal prices (panels 9a, 9b, and 9c) contracted abruptly in the first quarter of 2020 due to the collapse of global output, in turn caused by the initial pandemic containment measures. However, precious metals do not show the same pattern (panel 9d), as they are perceived globally as safe-haven assets. Later, energy and food prices recovered considerably due to post-pandemic disruptions in global supply chains. Metal prices also showed increases, although the latter moderated since end-2020 (with a reversion in the case of industrial metals).

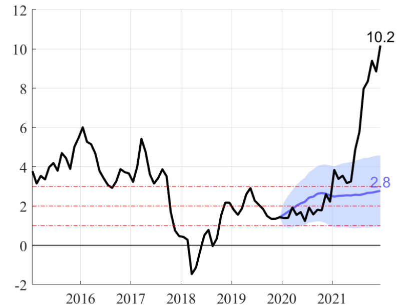
The counterfactual dynamics is consistent with the domestic variable forecasts (based on information as of 2019) for 2020 and 2021. Such forecasts are in line with the pre-pandemic predicted sequence for the external sector (red lines in Figure 9) and with the posterior distribution of the variables estimated for the whole sample. Figure 10 shows the results of this counterfactual exercise, where the black and blue lines represent the actual and counterfactual data, respectively; and the light blue area shows the 68% credible interval for the counterfactual estimation.

Figure 10. *Forecasts for Domestic Inflation Measures*

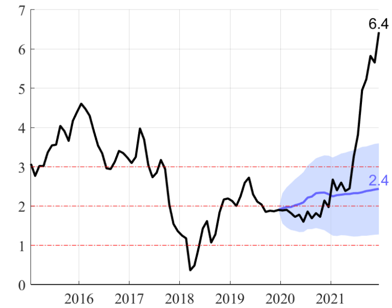
(a) *CPI-EFE*



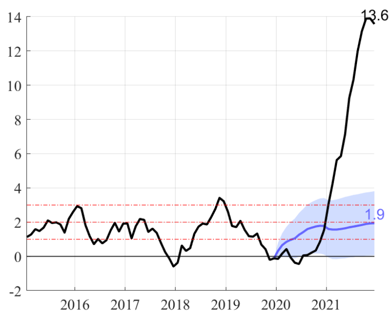
(b) *CPI-FE*



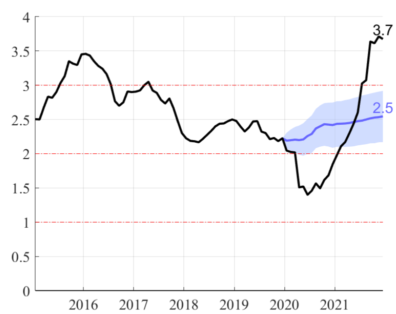
(c) *CPI*



(d) *WPI*



(e) *Expected CPI*



In general, the results of this exercise suggest that all measures of domestic inflation would have remained within the target band throughout 2020 and 2021. Although the risk of exceeding the target band is estimated to be reduced in this counterfactual scenario, the CPI-FE, WPI, and CPI inflation measures carry the highest risk, as suggested by their credible intervals (panels 10b, 10d, and 10c, respectively).

More specifically, panel 10a shows that CPI-EFE inflation would have remained close to 2%; i.e., a 1.0 p.p. difference relative to the observed data, above the confidence interval of the counterfactual scenario, as international commodity price shocks translated directly into CPI-EFE inflation. Regarding the central counterfactual estimation, Table 7 shows that, as of end-2020, interannual CPI-EFE inflation would have been 2.2% in the counterfactual exercise; i.e., 0.4 p.p. above the actual data reported by Peru's statistics agency (INEI). This trajectory reverts in 2021, when actual data exceed the counterfactual estimation, reaching 3.2% (1.0 p.p. above counterfactual inflation) as of end-2021.

Panel 10b shows that actual interannual CPI-FE inflation largely exceeds counterfactual inflation in 2021. Both follow similar trajectories in 2020, with counterfactual inflation remaining within the credible interval. However, actual CPI-FE inflation then soars abruptly, to 10.2% in December 2021 (Table 7), 7.4 p.p. above counterfactual inflation, suggesting that international inflation pressures largely explain the considerable CPI-FE inflation rate.

Therefore, as CPI inflation is a weighted average of the CPI-EFE and CPI-FE inflation rates, the dynamics presented in panel 10c considers elements from panels 10a and 10b. Along these lines, actual interannual CPI inflation in 2020 was slightly lower than counterfactual inflation (by 0.3 p.p.) and remained within the counterfactual estimation's credible interval until mid-2021. However, the rapid increase in CPI-FE inflation pushed CPI inflation above counterfactual inflation as of end-2021. Table 7 shows that, if the external block had remained within the pre-pandemic forecast, total inflation would have been half what it turned out to be as of December 2021 (6.4% vs. 2.4%).

Table 7. *Conditional Forecasts: Twelve-Month Percent Variation in Domestic Price Indices*

	D.20	J	F	M	A	M	J	J	A	S	O	N	D.21
CPI													
Observed	2,0	2,7	2,4	2,6	2,4	2,4	3,3	3,8	5,0	5,2	5,8	5,7	6,4
Counterfactual	2,3	2,2	2,3	2,3	2,3	2,3	2,3	2,3	2,4	2,4	2,4	2,4	2,4
EFE													
Observed	1,8	1,7	1,6	1,8	1,7	1,8	1,9	2,1	2,4	2,6	2,8	2,9	3,2
Counterfactual	2,1	2,1	2,1	2,1	2,1	2,1	2,1	2,1	2,1	2,1	2,1	2,2	2,2
FE													
Observed	2,2	3,8	3,4	3,5	3,2	3,3	4,9	5,8	8,0	8,4	9,4	8,9	10,2
Counterfactual	2,6	2,5	2,5	2,5	2,5	2,5	2,6	2,6	2,6	2,6	2,7	2,8	2,8
WPI													
Observed	1,6	3,0	4,2	5,6	5,9	7,1	9,2	10,3	12,0	13,1	13,9	13,9	13,6
Counterfactual	1,8	1,6	1,5	1,6	1,6	1,7	1,7	1,7	1,8	1,8	1,9	1,9	1,9
Expectations													
Observed	1,8	2,0	2,1	2,2	2,3	2,4	2,6	3,0	3,1	3,6	3,6	3,7	3,7
Counterfactual	2,4	2,4	2,4	2,4	2,4	2,5	2,5	2,5	2,5	2,5	2,5	2,5	2,5

In general, WPI inflation is directly influenced by the dynamics of international prices. Panel 10d shows that the counterfactual WPI forecast is stable and close to the inflation targer (although highly volatile). However, actual inflation contracts significantly in the first half of 2020 and experiences a considerable impulse thereafter, almost replicating the dynamics of non-metal commodity prices. As of end-2020 (Table 7), counterfactual WPI inflation is estimated at 1.8% (0.2 p.p. above actual IMP inflation). In contrast, as of December 2021, counterfactual inflation is estimated at 13.6 p.p. below actual inflation, reflecting the importance of external price dynamics on this measure of inflation.

In the case of inflation expectations, the conditional forecast (Figure 10e) suggests that inflation would have increased slightly and in a sustained manner, from 2% to 2.5% (above the target). However, the 68% credible interval for counterfactual inflation would have remained within the target band. However, actual values show a very different behavior, reflecting the influence of external conditions on the formation of expectations. In fact, in line with the dynamics of non-metal commodity prices, expectations decreased from March 2020 and accelerated abruptly from end-2020 throughout 2021. In this regard (Table 7), inflation expectations were 1.8% (0.6 p.p. below counterfactual expectations) as of end-2020. However, after this reversal, expectations reached 3.7% (vis-à-vis a counterfactual 2.5%) as of December 2021.

4 Conclusions

This research studies the dynamics of domestic inflation and its quantitative response to changes in commodity prices, the exchange rate, and inflation expectations, under a Bayesian approach to control for the proliferation of parameters and include the assumption of a small open economy. Additionally, structural shocks are identified using the least possible number of contemporaneous sign and zero restrictions. The latter result from foreign sector exogeneity and simultaneity, as suggested by economic theory regarding domestic variables.

The results of the exercise reveal interesting features in Peru's inflation dynamics over the last 15 years. The study concludes that non-metal commodity price shocks are persistent and inflationary, particularly international food prices. This is consistent with the literature on similar exercises for several economies. The higher the production costs (pushed by increased imported input prices), the higher the inflation identified by the model.

In contrast, international metal price shocks trigger a lower and less persistent inflation. In general, metal price increases improve Peru's commodity exports, in turn translating into better economic conditions, enhanced productive capacity, and higher aggregate output. This finding runs counter to the evidence in literature on advanced economies as, in the latter, metal price increases raise production costs, in turn translating into higher inflation.

Additionally, we estimated the dynamics of domestic inflation for 2020 and 2021 in line with the pre-pandemic international environment. This exercise illustrates the importance of the external sector in determining domestic inflation, as none of the measures used would have exceeded the target band if commodity prices had remained at the values predicted as of end-2019. Moreover, we estimate that the risk of exceeding the target band would have been reduced in this counterfactual context, although with a relatively higher risk for CPI-FE, WPI, and CPI inflation.

We also find significant and relatively persistent responses to exchange rate shocks. It is important to mention that the impact identified in this study is clearly greater to that found in previous research on the pass-through from depreciation to inflation. A result worth noting is the considerable contribution of non-metal commodity prices and nominal depreciation to inflation processes, which underscores the importance of following up on these variables for ensuring an effective inflation control.

An important limitation in this research is the exclusion of information drawn from economic activity or policy response variables. Adding these variables might improve the quality of the methodology for identifying structural shocks. However, the considerable variability since the pandemic outbreak could artificially alter the results, especially in the linear context used in this study. We stress that adding these kinds of variables to the information set and implementing an estimation and identification that are robust to this extraordinary variability is a top priority in our future research agenda.

Understanding inflation dynamics conditional to each kind of shock is key to monetary policy design, as shocks trigger substantially heterogeneous reaction patterns, thereby requiring differentiated policy responses in each case. Summing up, this study seeks to make a contribution to the literature by attempting to quantify such heterogeneity.

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A Transformations and Results

Transforming the data prior to estimation (in levels or differences) has implications for the assumptions about the interactions between variables and, consequently, for the results. Specifically, these transformations affect the moving average structure of the variables. This study seeks to identify the interannual price variations. Along these lines, this Annex focuses on the implications of transformations for estimating interannual log-variations.

First, we consider using level values for estimating the model. Thus, if y_t is the log of a given price index and x_t captures all other structural BVAR elements different from y_t, then the model and the transformation of interest take the form of equations (A.1) and (A.2), respectively. Therefore, an estimation using level values does not include moving averages in its specification; and the interannual variation involves an integrated moving average factor of order 12.

$$y_t = \sum_{i=1}^{p} A_i y_{t-1} + x_t \tag{A.1}$$

$$\Delta_{12} y_t = \sum_{i=1}^{p} A_i \Delta_{12} y_{t-i} + x_t - x_{t-12}. \tag{A.2}$$

If the estimation uses first differences, the model and the transformation of interest would be expressed as (A.3) and (A.4), respectively. The estimation assumes that the specification of the log-difference includes no average means. Therefore, the interannual variation involves an integrated mean average factor of order 12.

$$\Delta y_t \times F = \sum_{i=1}^{p} A_i \Delta y_{t-i} \times F + x_t \times F \tag{A.3}$$

$$\Delta_{12} y_t = (1 + A_1)\Delta_{12} y_{t-1} + \sum_{i=2}^{p} (A_i - A_{i-1})\Delta_{12} y_{t-i} - A_p \Delta_{12} y_{t-p-1} + x_t - x_{t-12}. \tag{A.4}$$

Finally, if the estimation is performed using interannual differences, the model and the transformation of interest coincide and can be expressed as (A.5). In this case, the estimation assumes that the specification of the interannual log-difference includes no average means.

$$\Delta_{12} y_t = \sum_{i=1}^{p} A_i \Delta_{12} y_{t-i} + x_t. \tag{A.5}$$

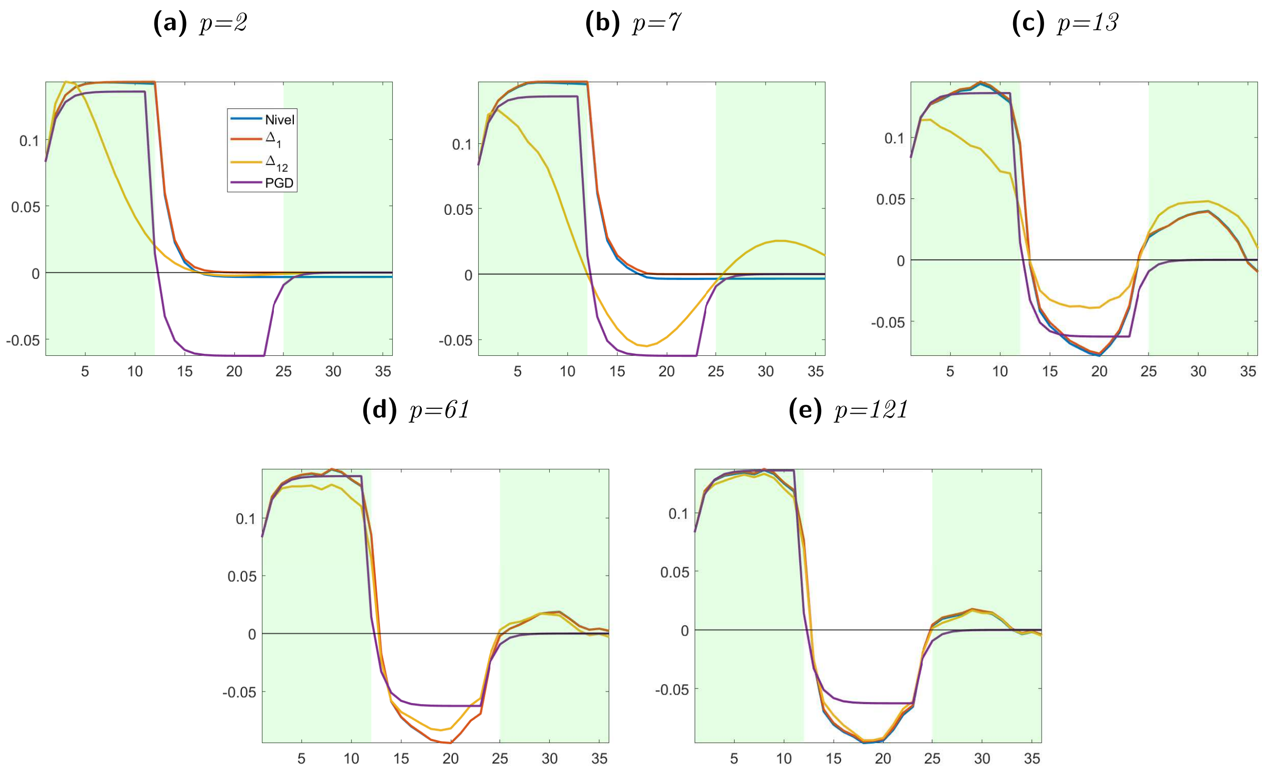
We perform the following simulation exercise to assess the implications for different data transformations:

1. We simulate 1000 observations from the following DGP: $y_t = (1+0.3867)y_{t-1} - 0.3867 y_{t-2} + u_t - 0.4595 u_{t-12}$ with $u_t \sim \mathcal{N}(0, 0.0485)$. This DGP corresponds to the model identified for the CPI log under the TRAMO segment of the TRAMO-SEATS filter developed by Bógalo (2004).

2. We estimate $AR(p)$ for different transformations of the simulated data (i.e., levels, first differences, and interannual differences) and different values of p to calculate the IRFs and the transformations of interest (i.e., interannual differences).

It is important to emphasize that, in this exercise, all estimations (regarding the transformations) have specification problems, as the (level) DGP includes an MA component and, therefore, the DGPs for the

Figure 11. *Interannual Variation Responses for Different Transformation Options*



(a) *p=2* **(b)** *p=7* **(c)** *p=13* **(d)** *p=61* **(e)** *p=121*

differences also include MA components. In contrast, we only estimate AR(p) processes, which is parallel to the VAR estimation, as it does not include MA components. Thus, all estimations in this Annex have constructions problems.

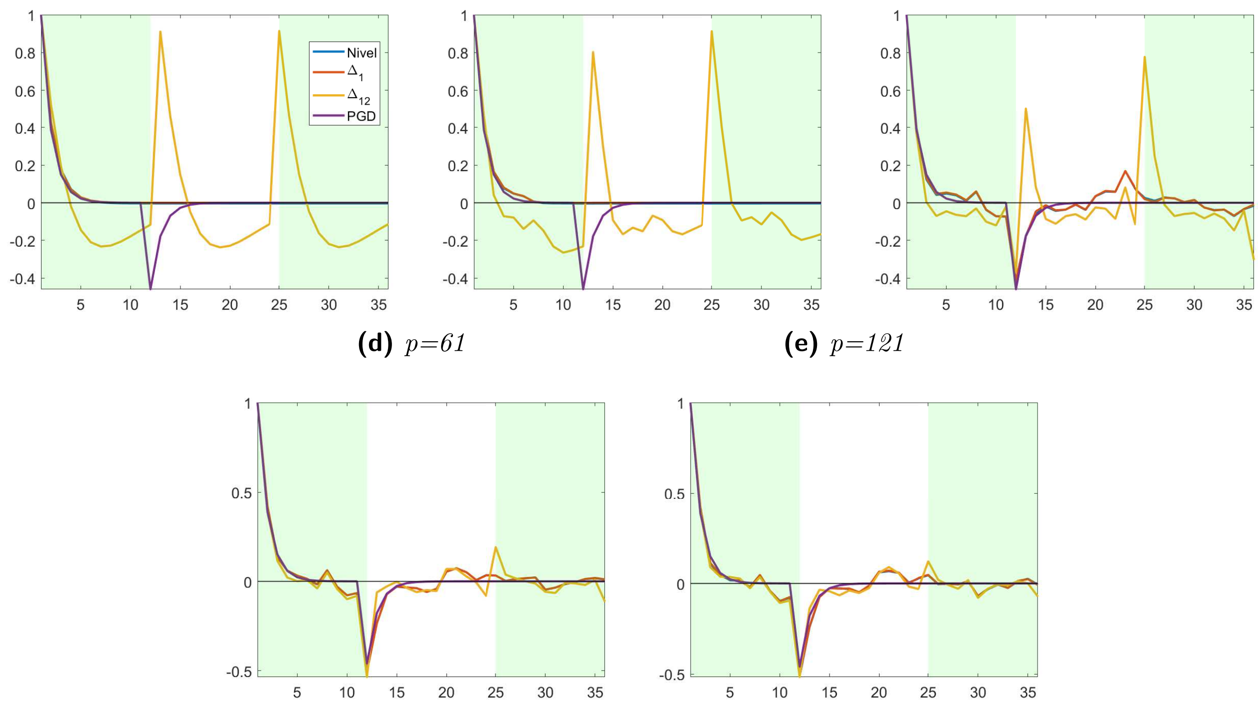
Figure (11) shows that the IRFs for the seasonal log-differences estimated using different assumptions for the transformations in the estimation. The actual IRF (derived from the DGP) is represented as a purple line in all panels. For their part, IRFs calculated with xxx in levels, first differences, or seasonal differences, are presented as blue, yellow, and red lines, respectively. Two results stand out in this simulation: first, the estimations in levels and first differences take less lags to come closer to the IRF from the DGP; and second, with a sufficiently large number of lags, the selection of the transformation in the estimation becomes largely irrelevant.

Figure (12) presents a similar exercise, but, unlike the previous figure, it reports the IRFs for the monthly variations. It should be noted that, if the focus is on monthly variations, it is better to use many lags as, in this way, the IRFs come closer to the DGP; and the cyclical component present in the estimation using interannual variations decreases. The cost of using several lags is that it introduces noise in the estimation and requires many observations.

Based on this simulation, it can be argued that it is preferable to use several lags, and that an estimation in levels or first differences is likely to provide a better fit. However, we highlight an important limitation: these illustrative results are not a general outcome, as we have not performed a formal convergence analysis. In fact, if the DGP had been designed so that the interannual difference does not include MA components, the best-performing estimation would be the one using a 12-month difference.

In practice, it is difficult to know ex ante whether the data transformation excludes MA components in its DGP,

Figure 12. *Monthly Variation Responses for Different Transformation Options*



(a) *p=2* **(b)** *p=7* **(c)** *p=13* **(d)** *p=61* **(e)** *p=121*

or if none of them does (like the DGP simulated in this Annex). In light of this uncertainty, the election of the transformation must result from a balance between the convergence statistical features and the capacity to yield results of economic relevance. Along these lines, we chose to carry out the estimation with interannual variations with several lags (i.e., $p = 13$).[14] With 13 lags, the IRFs are expected to come close to the DGP with some error margin (according to the results of the simulation described in this Annex). However, the results (for both the IRFs and the HD) lend themselves better to an economic narrative of the events in the sample (Section 3).

B Pass-Through vs. Impulse-Response Function

To illustrate the point that a greater PT does not imply greater responses from the variable of interest, we simulate two stochastic processes with different PT sequences.

The first process (in (B.1)) is specified as a stationary VAR(2) with a constant PT equal to 0.75:

$$\begin{aligned}
&\begin{bmatrix} y_{1,t} \\ y_{2,t} \end{bmatrix} = \begin{bmatrix} 1.44 & 0 \\ 0 & 1.44 \end{bmatrix} \begin{bmatrix} y_{1,t-1} \\ y_{2,t-1} \end{bmatrix} + \begin{bmatrix} -0.55 & 0 \\ 0 & -0.55 \end{bmatrix} \begin{bmatrix} y_{1,t-2} \\ y_{2,t-2} \end{bmatrix} + \begin{bmatrix} \epsilon_{1,t} \\ \epsilon_{2,t} \end{bmatrix} \\
&\text{con } \begin{bmatrix} \epsilon_{1,t} \\ \epsilon_{2,t} \end{bmatrix} \sim \mathcal{N}\left(\mathbf{0}, \mathbf{CC}'\right) \text{ where } \mathbf{C} = \begin{bmatrix} 1 & 0 \\ 0.75 & 1 \end{bmatrix}.
\end{aligned} \tag{B.1}$$

The second process (in (B.2)) is specified as a stationary VAR(2) with a long-term PT of 0.75. In this process,

[14] Figure (11) suggests that it is likely to identify marked inflection points along the IRFs in the year of the shock.

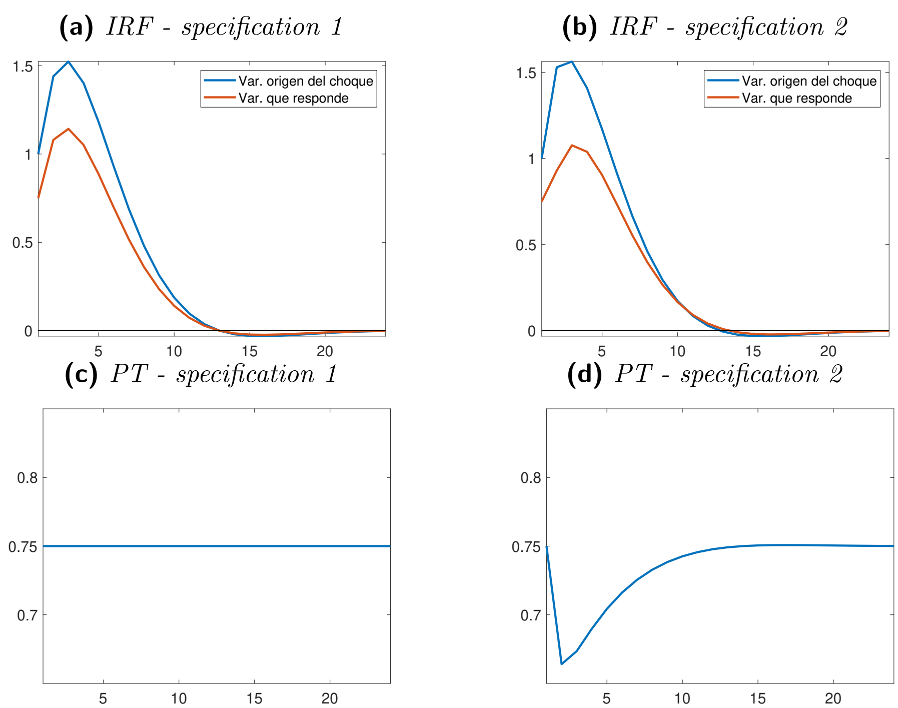
the PT contracts temporarily but recovers later to its long-term value:

$$\begin{bmatrix} y_{1,t} \\ y_{2,t} \end{bmatrix} = \begin{bmatrix} 1.44 & 0.12 \\ -0.15 & 1.44 \end{bmatrix} \begin{bmatrix} y_{1,t-1} \\ y_{2,t-1} \end{bmatrix} + \begin{bmatrix} -0.55 & -0.12 \\ 0.15 & -0.55 \end{bmatrix} \begin{bmatrix} y_{1,t-2} \\ y_{2,t-2} \end{bmatrix} + \begin{bmatrix} \epsilon_{1,t} \\ \epsilon_{2,t} \end{bmatrix}$$
$$\text{con } \begin{bmatrix} \epsilon_{1,t} \\ \epsilon_{2,t} \end{bmatrix} \sim \mathcal{N}\left(\mathbf{0}, \mathbf{CC}'\right) \text{ where } \mathbf{C} = \begin{bmatrix} 1 & 0 \\ 0.75 & 1 \end{bmatrix}. \tag{B.2}$$

Figure (13) shows the IRFs and PTs for the processes in equations (B.1) and (B.2). Column 1 in (13) (i.e., panels (13a) and (13c)) shows the results for specification (B.1). A shock in $y_{1,t}$ generates a response in $y_{1,t}$ and $y_{2,t}$, which dissipates over time; i.e., after 20 periods there is no observable variation in the endogenous variables resulting from the shock (see IRF). On average, variable $y_{2,t}$ with a 75% intensity at all moments (see PT). It is worth noting that, even when the IRF shows no response (from period 20), the PT is positive and equal to 0.75.

Similarly, column 2 in (13) (i.e., panels (13b) and (13d)) shows the results for specification (B.2). A shock in $y_{1,t}$ generates a response in $y_{1,t}$ y $y_{2,t}$, which also dissipates in around 20 periods (see IRF). On average, during year 1 of the shock, variable $y_{2,t}$ responded with less than 75% intensity. The latter grows to close to 75% around 15 months after the shock (see PT). It should be noted that the PT grows between periods 3-15, but the IRF decreases over the same time. Therefore, PT increases may occur even when the effects from the shock dissipate. The best measure for predicting a greater response to a given shock is the IRF instead of the PT.

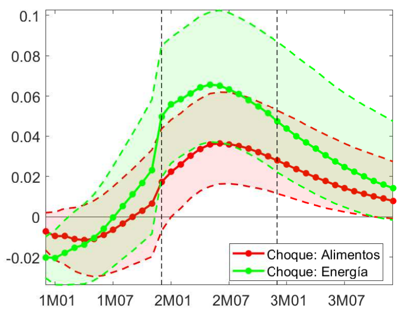
Figure 13. *Responses and Pass-Through in the Simulation Exercise*



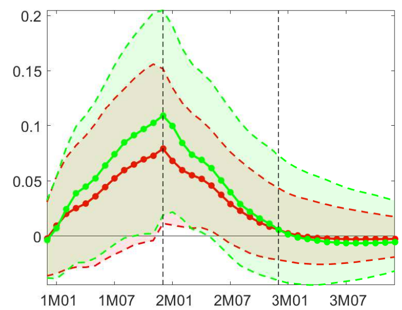
C Results for other Specifications

Figure 14. *Estimation in Differences: Interannual Inflation Responses to Non-Metal Price Shocks*

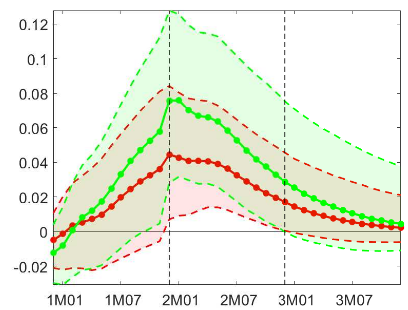
(a) *CPI-EFE*



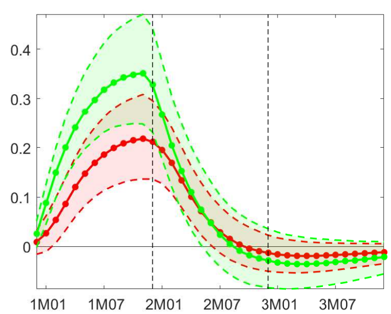
(b) *CPI-FE*



(c) *CPI*



(d) *WPI*



(e) *Expected CPI*

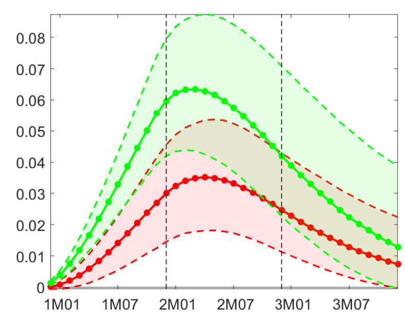


Figure 15. *Estimation in Levels: Interannual Inflation Responses to Non-Metal Price Shocks*

(a) *CPI-EFE* **(b)** *CPI-FE* **(c)** *CPI*

(d) *WPI* **(e)** *Expected CPI*

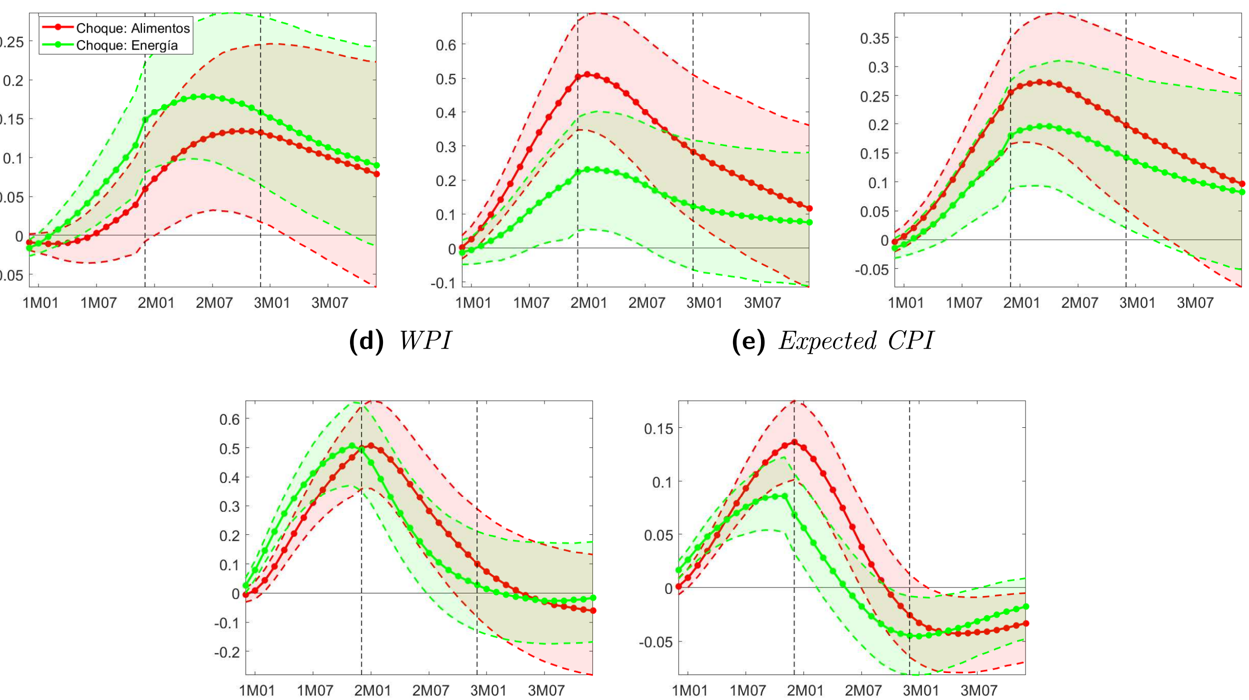
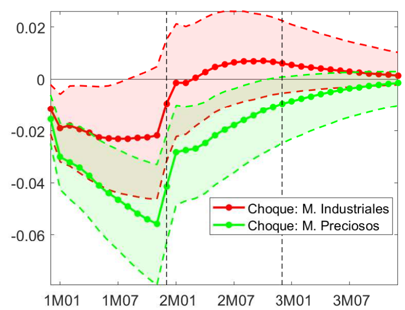
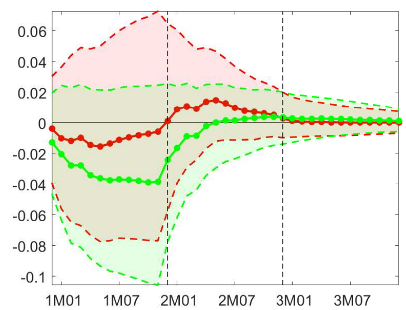


Figure 16. *Estimation in Differences: Interannual Inflation Responses to Non-Metal Price Shocks*

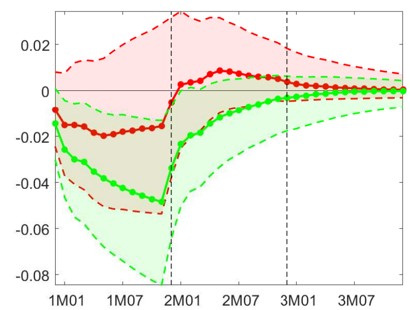
(a) *CPI-EFE*



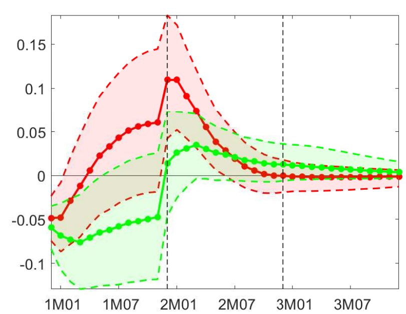
(b) *CPI-FE*



(c) *CPI*



(d) *WPI*



(e) *Expected CPI*

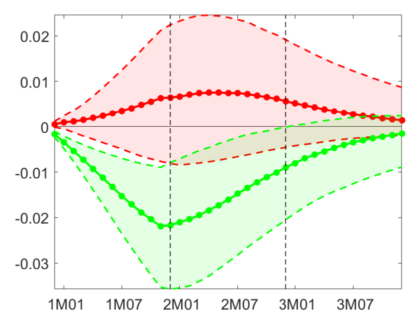
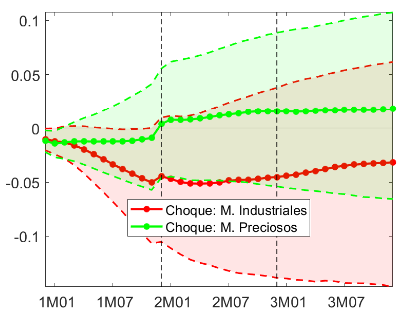
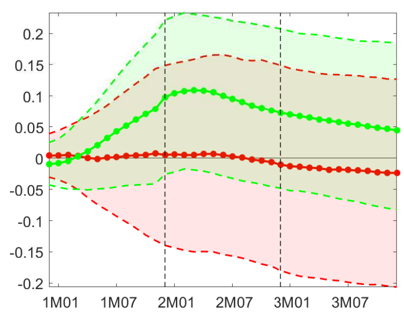


Figure 17. *Estimation in Levels: Interannual Inflation Responses to Non-Metal Price Shocks*

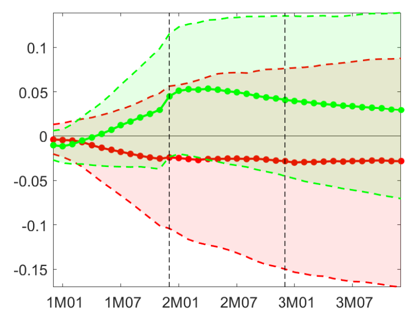
(a) *CPI-EFE*



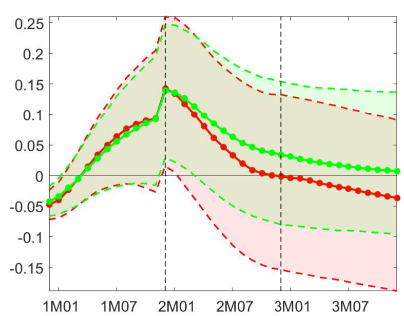
(b) *CPI-FE*



(c) *CPI*



(d) *WPI*



(e) *Expected CPI*

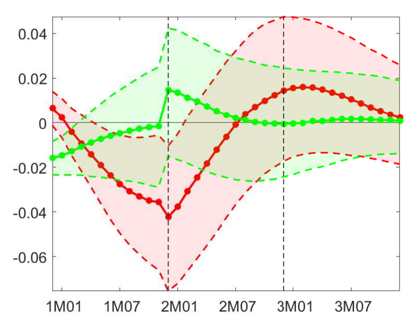
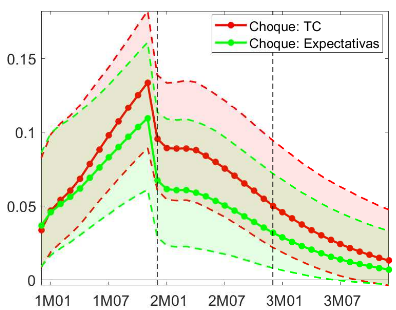
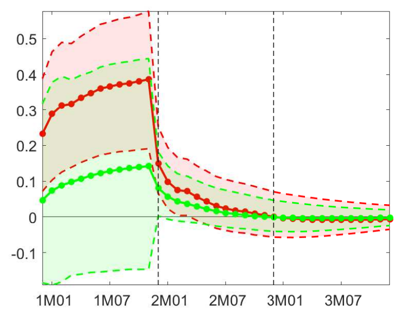


Figure 18. *Estimation in Differences: Interannual Inflation Responses to Non-Metal Price Shocks*

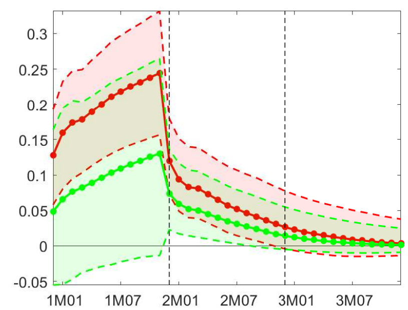
(a) *CPI-EFE*



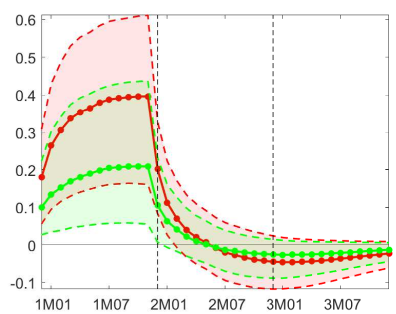
(b) *CPI-FE*



(c) *CPI*



(d) *WPI*



(e) *Expected CPI*

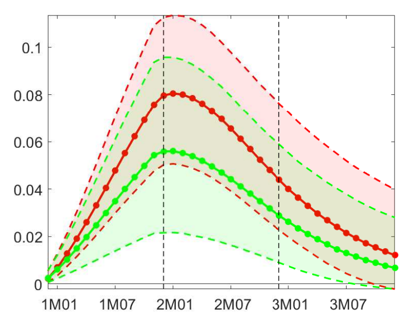


Figure 19. *Estimation in Levels: Interannual Inflation Response to Non-Metal Price Shocks*

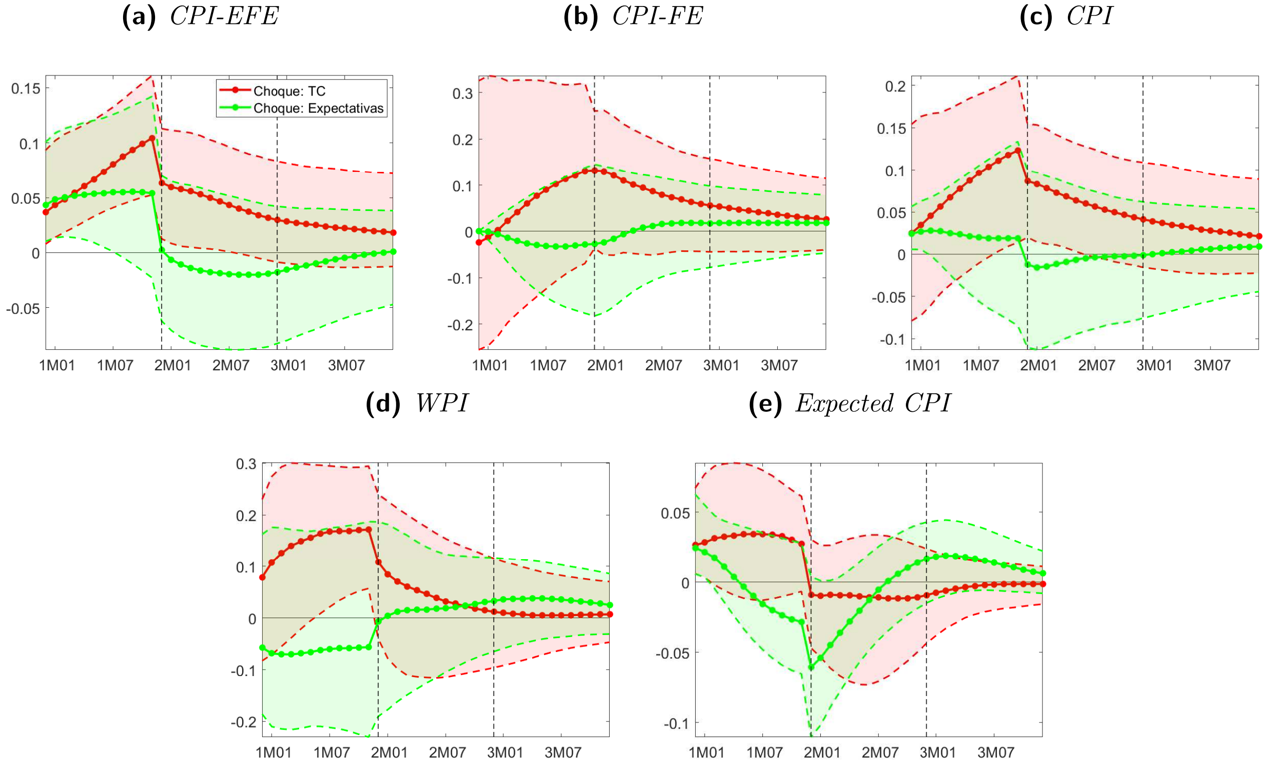


Figure 20. *Estimation in Differences: Historical Decomposition of Interannual CPI Inflation*

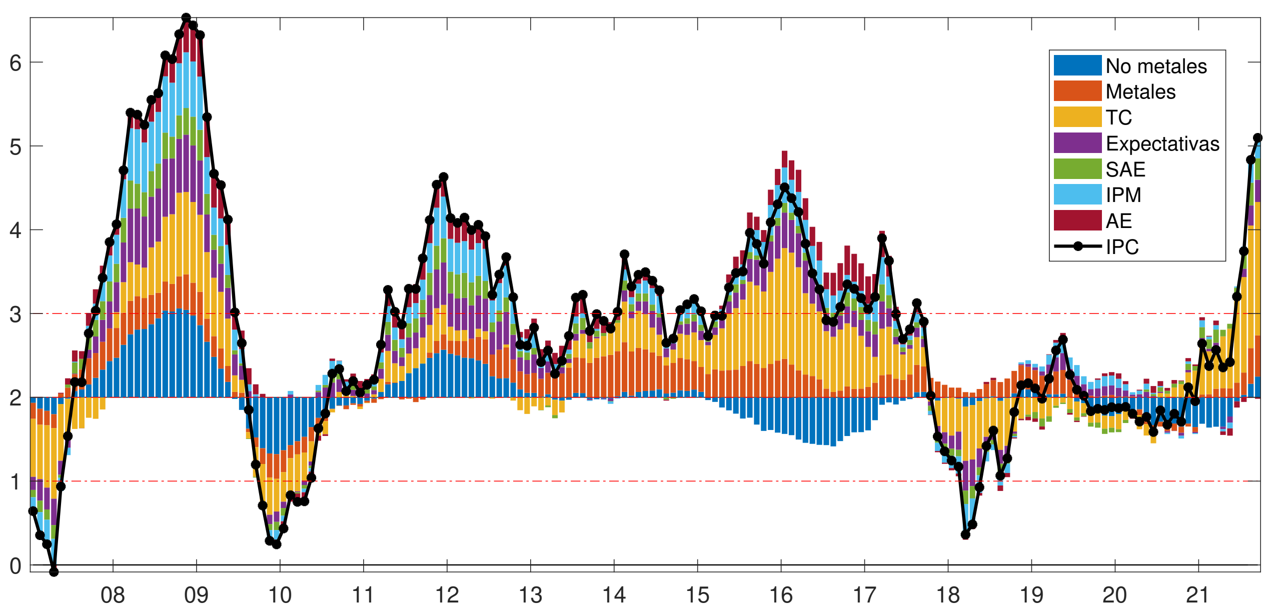


Figure 21. *Estimation in Levels: Historical Decomposition of Interannual CPI Inflation*

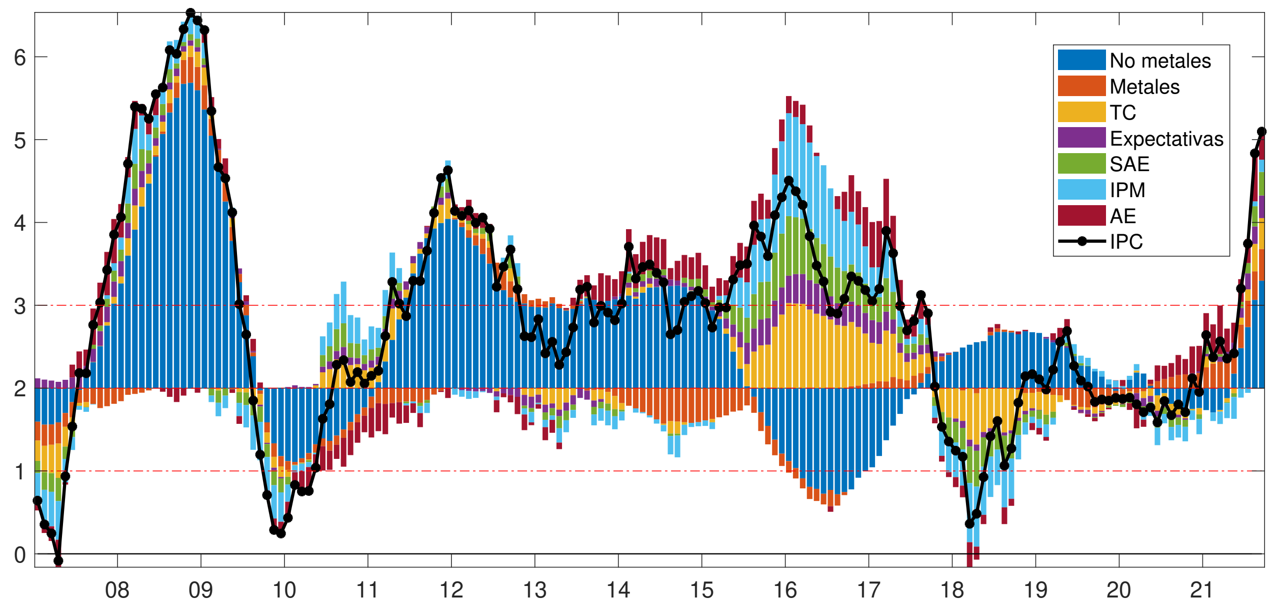


Figure 22. *Estimation in Differences: Historical Decomposition of Interannual CPI-EFE Inflation*

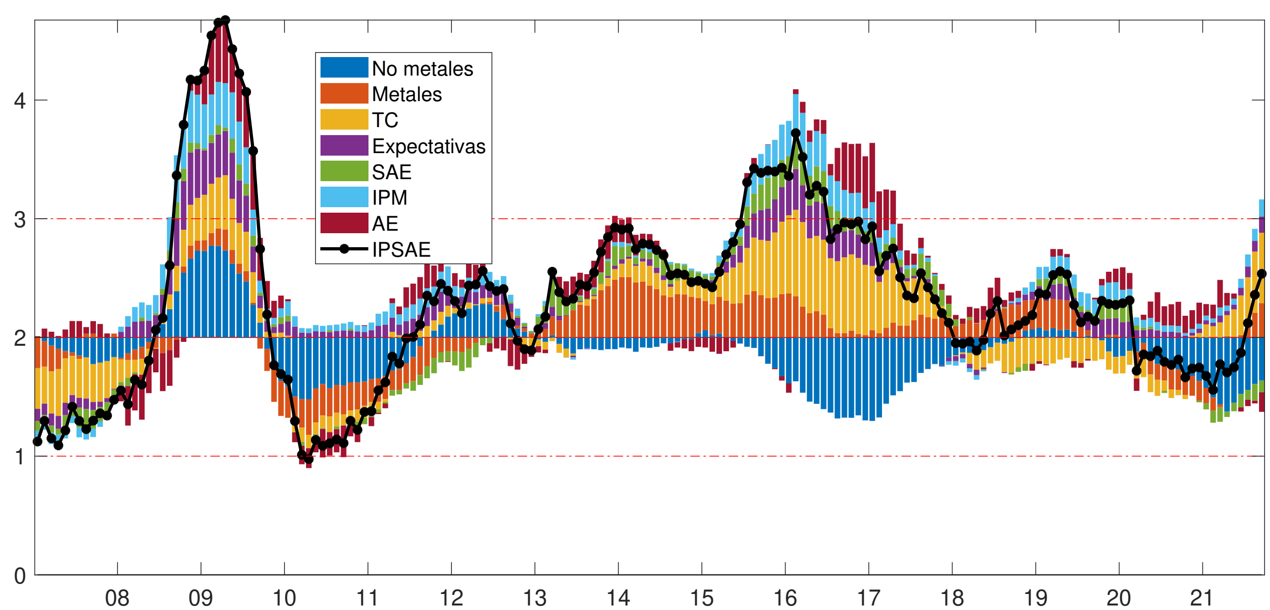


Figure 23. *Estimation in Levels: Historical Decomposition of Interannual CPI-EFE Inflation*

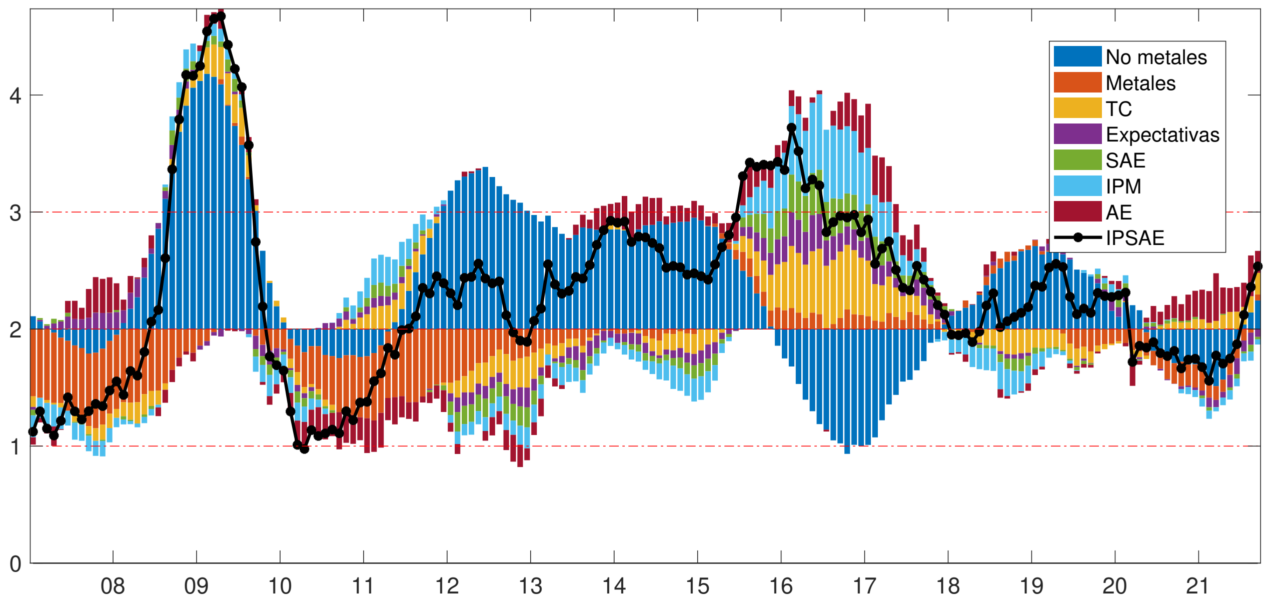


Figure 24. *Estimation in Differences: Historical Decomposition of Interannual CPI-FE Inflation*

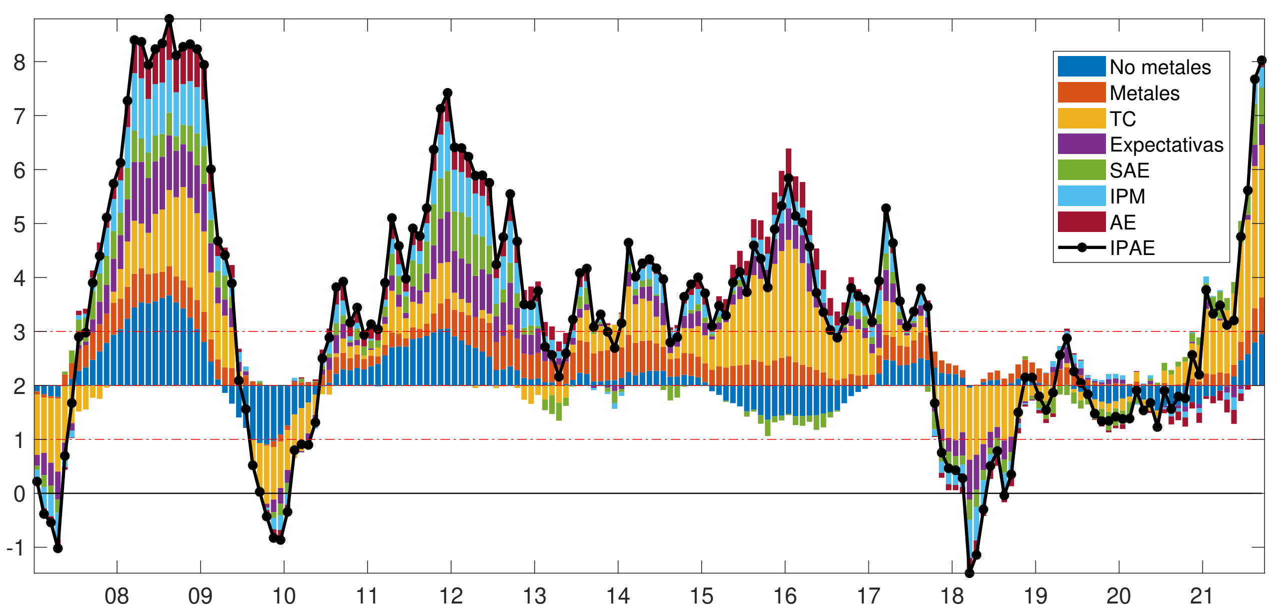
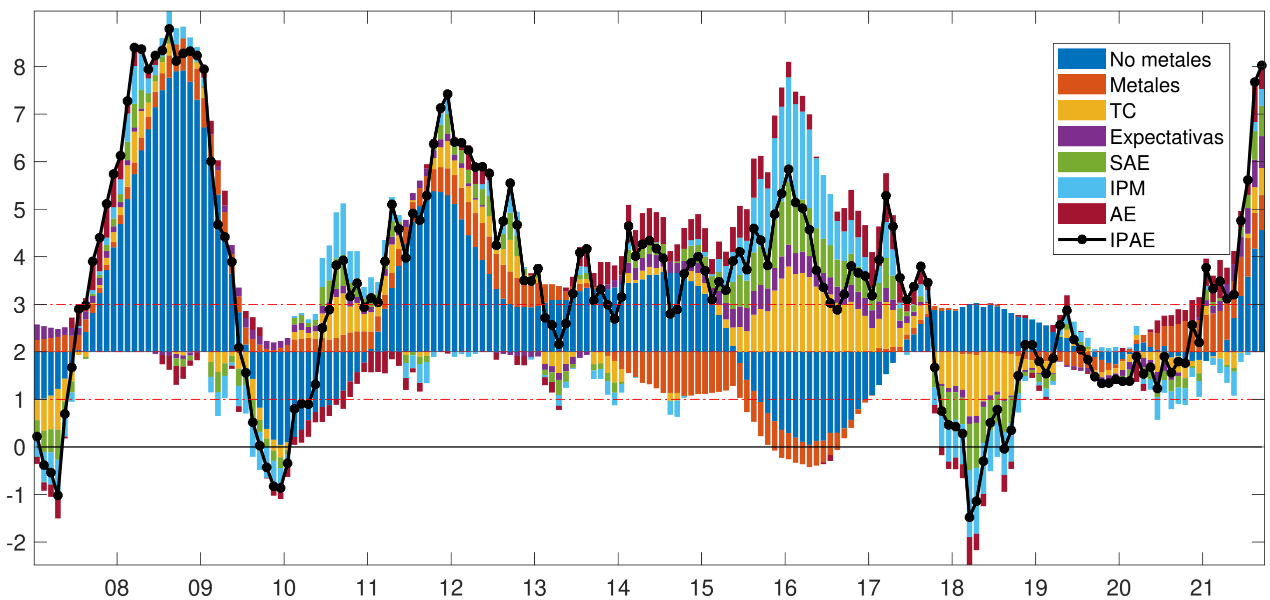


Figure 25. *Estimation in Levels: Historical Decomposition of Interannual CPI-FE Inflation*



D Robustness Exercise

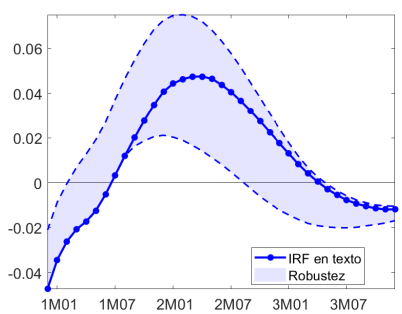
This section assesses the sensitivity of the results from changes in the ordering suggested in (2.5) for the four external variables. Figures 26-29 show the modal IRFs for each case presented in Figures 3-5. The areas in Figures 26-29 correspond to the maximum and minimum IRFs estimated with the $4! = 24$ possible orderings for (2.5).

The most robust shocks correspond to responses to international food price shocks (Figure 27), followed by responses to energy price shocks (Figure 26). In the latter case, the response of the CPI-FE (and, by construction, the CPI) shows some robustness problems, showing positive and negative responses to different orderings of (2.5).

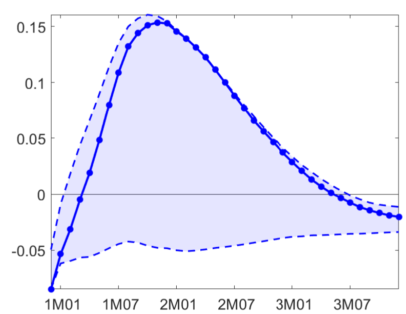
The responses to metal price shocks (Figures 28 and 29) merit some comments. In the former case, the WPI response turns out to be the least robust. In the latter case, the results are robust, although it should be noted that the ordering in (2.5) yields, in general, the least negative responses.

Figure 26. *Robustness - IRF for Different External Sector Orderings: Energy Price Shock*

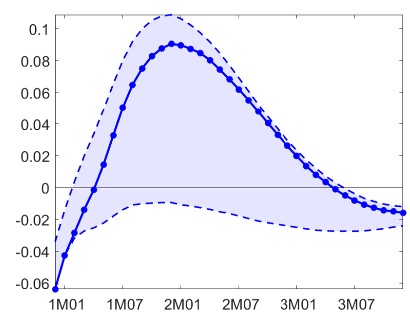
(a) *CPI-EFE*



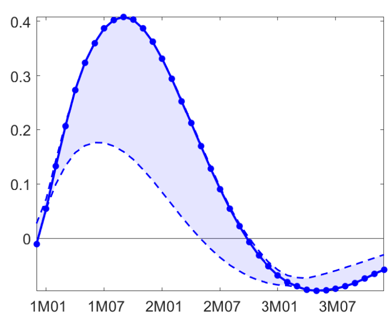
(b) *CPI-FE*



(c) *CPI*



(d) *WPI*



(e) *Expected CPI*

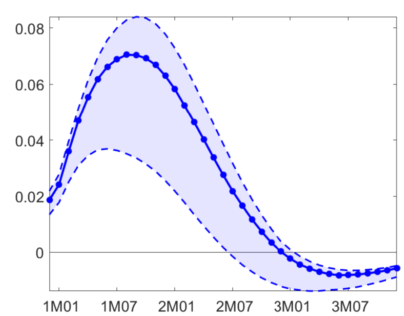
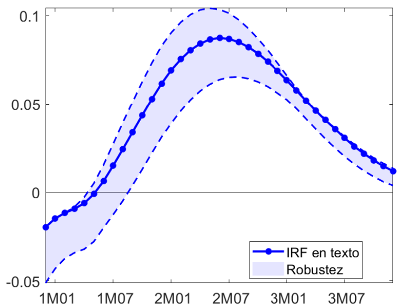
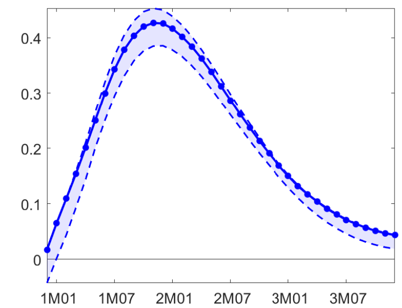


Figure 27. *Robustness - IRF for Different External Sector Orderings: Food Price Shock*

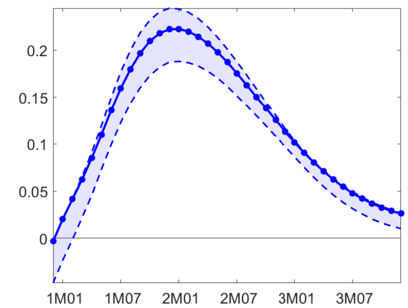
(a) *CPI-EFE*



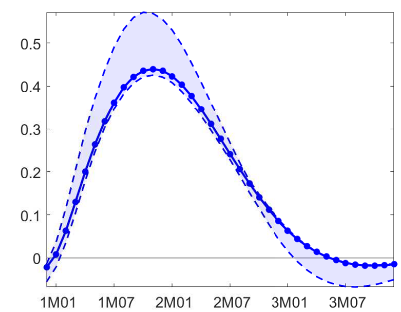
(b) *CPI-FE*



(c) *CPI*



(d) *WPI*



(e) *Expected CPI*

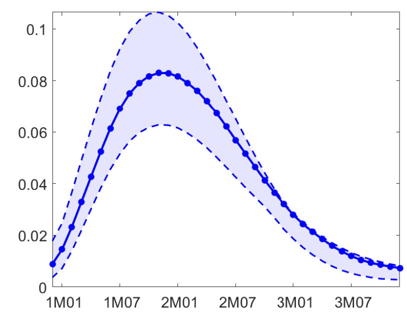
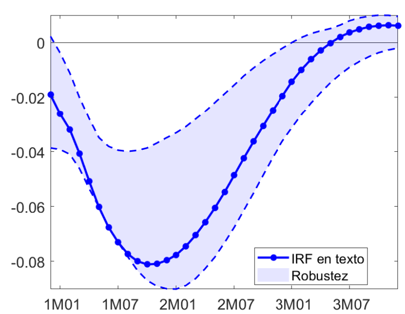
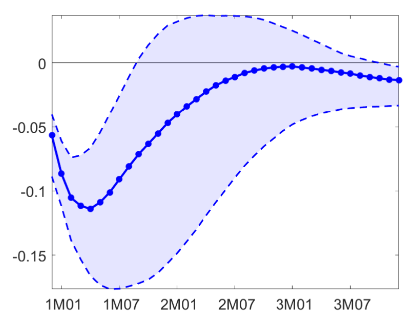


Figure 28. *Robustness - IRF for Different External Sector Orderings: Industrial Metal Shock*

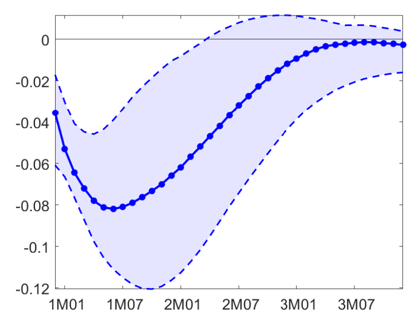
(a) *CPI-EFE*



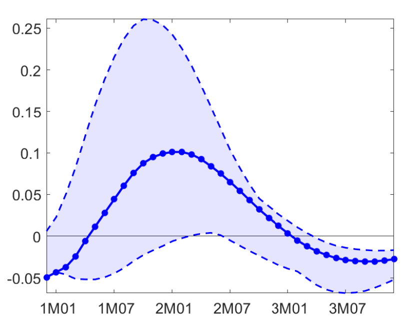
(b) *CPI-FE*



(c) *CPI*



(d) *WPI*



(e) *Expected CPI*

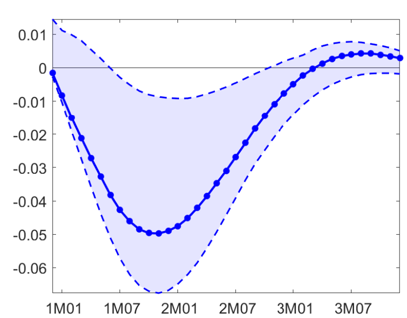


Figure 29. *Robustness - IRF for Different External Sector Orderings: Precious Metal Shock*