Fuel-price Shocks and Inflation in Latin America and the Caribbean

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Abstract[1]

We estimate the impact of fuel-commodity price shocks on inflation and inflation expectations for eight Latin American countries in which monetary policy follows inflation-targeting frameworks. We use Bayesian Vector Autoregressive models (BVARs) and data from 2005 and up to 2022 to quantify these impacts. We find that the fuel-price shocks are significant in all cases and the response ranges between 0.01 and 0.04 percentage points of inflation, following a 1 p .p. shock to fuel prices. A variance decomposition exercise shows that more than 50% of the outburst in inflation that these countries experienced in 2021 and 2022 can be attributed to the shock in global fuel prices. These results are robust to changes in the specification that include additional controls, different commodity price measures, different lag structures, and alternative ordering.

JEL classifications: E31, E52, Q43

Keywords: Fuel prices, Inflation, Inflation expectations, Latin America

[1] The views in this paper are solely the responsibility of the authors and should not be interpreted as representing the views of the Inter-American Development Bank, its Executive Board, or its Management. We thank Ana Cepeda, Martha Elena Delgado, and Santiago Novoa for excellent research assistance.

1 Introduction

Inflation tends to move in tandem around the world suggesting that common global factors are a key determinant of its dynamics.[2] The recent rise in inflation since the end of most of the lockdowns due to the COVID-19 pandemic has been closely linked to the rise in oil prices attributed both to the demand rebound following the re-opening of the economies and the invasion of Russia to Ukraine, and disruptions in the global supply chain, reflected in part in stark rises in shipping costs.

The literature has explored in great detail the role played by oil-price shocks in determining consumer price inflation in advanced and emerging economies. Several papers have placed efforts into quantifying the pass-through of oil and shipping prices to domestic prices. While results vary notably depending on the sample of countries used by authors, the time frame considered, and the methodologies used to estimate them, most of them lie within a range of a 0.01-0.08 p.p. response of inflation to a 1 p.p. shock in fuel prices.

In this paper, we estimate the impact of fuel-price shocks on inflation in eight Latin American and Caribbean countries that have inflation-targeting frameworks for their monetary policy. To quantify the impacts of global fuel-price shocks we use Bayesian-VAR models. They allow us to identify an exogenous fuel-price shock in a multi-variable model, considering a long lag structure while minimizing over-fitting concerns typical of this literature. The relevance of inflation expectations in the inflation-targeting regime is key to our story and that is why we focus only on countries that follow it.[3]

In our baseline specification, we estimate the impact of fuel commodity price shocks on inflation, controlling for inflation expectations and currency depreciation, and find that the magnitude of the inflation response varies across countries. On average, a 1 p.p. increase in the growth rate of fuel commodity prices rises the rate of inflation by 0.025 p.p after 12 months, with a minimum of 0.013 p.p. in Brazil, and a maximum of 0.04 p.p. in Chile. These numbers are sizable considering that fuel prices are very volatile. After the invasion of Russia into Ukraine in March 2022, fuel prices increased by 133 percent compared to March 2021. In terms of our estimates, this implies a 3.4 p.p. increase in inflation in the average country, a 5.4 p.p. increase in the maximum, and a 1.8 p.p. in the minimum. The results are in line with previous literature's findings.

The dynamics of the CPI inflation response also vary from country to country. On average, the maximum impact is reached at 12 months, but our estimates suggest that this can be between 5 and 20 months depending on the country. We also carry out inflation historical decomposition exercises and find that in recent years, changes in fuel prices explain at least half of the increase registered in CPI inflation.

A key issue for countries with an inflation-targeting regime lies in how changes in fuel prices affect inflation expectations. According to our estimates, inflation expectations are also strongly affected by fuel-price shocks. As with headline inflation, we find that fuel-price shocks have a somewhat persistent effect on expectations and that they explain more than half of the stochastic variation in inflation expectations since 2021. This is of great relevance for the design of monetary policy since it implies that global price shocks, even if temporary and exogenous, call for a strong policy response to avoid that expectations de-anchor, and inflation targets are not met.

We perform a battery of robustness tests that show that our main results hold regarding the impact of fuel-price changes on inflation dynamics in Latin American countries. First, we control

[2] See for example Ha et al. (2019) for a discussion.

[3] Our empirical specification is similar to that of Kilian and Zhou (2022).

for additional external factors such as shipping costs, that have been signaled recently as main determinants of global inflation.[4] Second, we control for an imperfect measure of the output gap based on monthly indicators of economic activity, to capture specifically dynamics associated with excess demand. Third and fourth, we alter the lag length and the order of variables in the specification to capture specific modeling issues that could alter the results. Our baseline results are consistently robust.

The paper is organized as follows. Section 2 presents a summary of the literature. Section 3 describes the methodology used, and Section 4 the data. Sections 5 and 6 report our main findings and the robustness exercises. We conclude in section 7.

2 Related Literature

Several papers have explored how global energy prices affect domestic inflation in a variety of settings. Regardless of the empirical model, the literature agrees on several channels through which this effect happens. First, an increase in energy prices can have a direct effect on domestic-fuel prices which account for a significant share of production costs. The rise in production costs affects consumer prices. Even if domestic fuel prices do not increase after a global fuel-price shock, because countries may implement mechanisms to smooth them, if the price of imported goods increase because of this same channel occurring abroad, the global shock will end up affecting domestic inflation.[5] Second, via inflation expectations. Inflation expectations may react to an increase in fuel prices and this, in turn, may lead to different types of contracts such as wage or credit contracts to incorporate higher levels of expected inflation and through this increase actual inflation.[6] Third, when faced with a fuel price shock workers may demand either higher wages or subsidies to compensate for the increase in fuel expenditure and transport costs. Higher household income may turn to higher aggregate demand and eventually inflation.[7]

The empirical literature that quantifies the impact of fuel price changes on inflation is abundant and we do not pretend to provide a thorough review here. Papers have used various approaches and diverse data sets to provide some estimates on the response of inflation to fuel-price shocks. While most of the literature has focused on advanced economies, a few research pieces have included at least some of the countries studied here.

Many papers base their estimations on augmented Phillips curves and focus on the United States, European countries, and Japan, and tend to find a significant impact of global-fuel prices on inflation.[8] Findings suggest that the impact has decreased over time when comparing the 2000s with the 1970s and 1980s and that it depends on the monetary policy stance of each country. Estimates oscillate between 0.01 and 0.08 p.p. increase following a 1% increase in global oil prices.

Several studies combine advanced economy with emerging market data. Example of this literature are Ha et al. (2019), Choi et al. (2018), Gelos and Ustyugova (2017), Salisu et al. (2017), Habermeier et al. (2009), and De Gregorio et al. (2007). As above they find significant impacts of fuel-price shocks on inflation that have been declining over time when comparing the 2000s with the

[4] See for example Carrière-Swallow et al. (2022)

[5] See Conflitti and Luciani (2019) for a discussion.

[6] The impact of oil prices on inflation expectations has been studied among others by Wong (2015) and Conflitti and Cristadoro (2018). A discussion of this mechanism is found in Conflitti and Luciani (2019) and De Gregorio et al. (2007).

[7] See Blanchard and Gali (2007) for a discussion.

[8] Examples are found in Kilian and Zhou (2022), Conflitti and Luciani (2019), Alvarez et al. (2011), Clark and Terry (2010), Chen (2009), LeBlanc and Chinn (2004), Hamilton (2003), and Hamilton (1983).

1980s. De Gregorio et al. (2007) find that the reduction in the pass-through is stronger in advanced economies, and that the pass-through is on average 30% higher in emerging economies. Salisu et al. (2017) divide countries between oil importers and exporters and finds that the pass-through is higher in the latter. Habermeier et al. (2009) also find a significant pass-through though they highlight that the role of monetary policy, and particularly having an independent central bank and an inflation targeting regime reduces the size of the pass-through.[9] The size of the pass-through in these studies that incorporate a wider diversity of countries also varies, with numbers varying between 0.01 in the case of Habermeier et al. (2009) and 0.05 as in Ha et al. (2019) following a 1% increase in the price of oil.

The methodologies used and the time spans considered vary as much as the sample of countries analyzed in the literature. Single equation estimations, panel data methods, country-specific VARs, panel VARs among others have been considered. As detailed in the following section, here we use country-specific Bayesian VAR models in the tradition of Kilian and Zhou (2022) and Clark and Terry (2010).

3 Methodology

We estimate the impact of changes in global fuel commodity prices on inflation and inflation expectations for 8 Latin American countries with inflation-targeting regimes: Brazil, Chile, Colombia, Costa Rica, Dominican Republic, Mexico, Paraguay, and Peru. To do this, for each country we estimate structural vector autoregressive (VAR) models of the relationship between the fluctuation of the global prices of fuel commodities and domestic variables: headline inflation, inflation expectations, and the nominal exchange rate depreciation. The model recognizes that international-fuel prices are exogenous to the domestic variables, and considers joint dynamics of the country-specific variables.

The time frame and the sample of countries are consistent with previous findings in the literature. We focus exclusively on countries with an inflation-targeting regime that according to Habermeier et al. (2009) have a similar pass-through, and we choose a time period that not only coincides with data availability as described in the next section, but that also ensures that it is homogeneous enough to avoid capturing the time-varying trend reduction in the pass-through documented in the literature.

The main structure of the VAR models is as follows. Let $y_t = [\Delta fuel_t, \pi_t, \Delta NER_t, \pi_t^E]'$, where $\Delta fuel_t$ denotes the 12-month increase in an index of the price of fuel commodities, π_t is the 12-month rate of inflation, ΔNER_t is the 12-month depreciation rate of the nominal exchange rate of the domestic currency against the US dollar, and π_t^E are 12-month ahead inflation expectations. The sample is determined by the availability of the inflation expectations data.[10] Our specification is inspired in Kilian and Zhou (2022), adding an exchange rate term to acknowledge potential exchange rate pass-through effects.[11]

We estimate the model using a conservative number of 6 lags and postulate that the first variable of the vector is exogenous, meaning that it is independent of the country-specific variables, but is allowed to follow its own specific autoregressive dynamic. Formally, our general model takes the

[9] It is worth noting that Gelos and Ustyugova (2017) find that the monetary policy regime does not seem to affect the magnitude of the pass-through.

[10] Inflation expectations is included following Kilian and Zhou (2022), Wong (2015), and Conflitti and Cristadoro (2018).

[11] In line with De Gregorio et al. (2007).

following form:

$$y_t = A_1 y_{t-1} + A_2 y_{t-2} + ... + A_p y_{t-p} + \mu_t, \tag{1}$$

where $t = 1, 2, ..., T$, p is the number of lags, and $\mu \sim N(0, \Sigma)$. To ensure exogeneity of $\Delta fuel_t$ we assume that the coefficients of the A_j matrices that relate the first two variables of the y_j with the rest of the system are equal to zero. So the typical A_j matrix, for each j between 1 and p has the following form:

$$A_j = \begin{pmatrix} a_{11}^j & 0 & 0 & 0 \\ a_{21}^j & a_{22}^j & a_{23}^j & a_{24}^j \\ a_{31}^j & a_{32}^j & a_{33}^j & a_{34}^j \\ a_{41}^j & a_{42}^j & a_{43}^j & a_{44}^j \end{pmatrix}. \tag{2}$$

We can re-write Equation (1) in a more compact notation as

$$y_t = A(L)y_t + \mu_t$$

or

$$\theta(L)y_t = \mu_t. \tag{3}$$

We include additional structure by assuming that the innovations or prediction errors (μ) are related to structural errors (ϵ) following:

$$\mu_t = C\epsilon_t, \tag{4}$$

where C is the Cholesky decomposition of $\hat{\Sigma}$. Under this structure, we pose that fuel prices are not affected contemporaneously by the country-specific endogenous block and that inflation is the most exogenous of the domestic variables meaning that it does not respond contemporaneously to other domestic variables, while inflation expectations may respond contemporaneously to all variables in the system.

The model comprised of Equations (2), (3), and (4) can be estimated either by maximizing the likelihood function derived from the assumption of residual normality, or using Bayesian techniques. Especially in small samples, Bayesian methods are preferred because they allow inference to be carried out conditional on the sample size and other characteristics of the sample, reducing the uncertainty associated with the values of the estimated parameters and avoiding the problems resulting from over-fitting models.[12]

In addition, Bayesian methods also facilitate the computation of moments not only for the parameters but also for functions derived from them, including impulse response functions and historical decomposition.[13]

A key element for doing a Bayesian estimation is the choice of the prior distribution of the model parameters. Here we use an independent normal-Wishart prior that assumes that the parameters of the model follow a multivariate normal distribution and that the residual variance-covariance

[12] The Bayesian approach assumes that every parameter is a random variable following a distribution that ought to be identified by the econometrician to carry out inference. This differs from the maximum likelihood approach, also known as the frequentist approach, which assumes that there exist true parameter values to be estimated.

[13] See Koop (1992) for a discussion of Bayesian methods providing exact finite sample density for both the parameters and their functions.

matrix (Σ) is unknown. By using the independent normal-Wishart prior we reduce restrictions on the structure of the covariance matrix and can estimate it using Gibbs sampling.[14]

To ensure the exogeneity of fuel prices ($\Delta fuel_t$), we set a prior equal to 0 to the relevant coefficients in the matrix defined in Equation (2) and assign an arbitrarily small variance on them to make sure that the posterior distributions remain with values very close to zero.

For each of the eight countries, we estimate this B-VAR and their corresponding impulse response functions over 2,000 iterations of the underlying Gibbs sampling algorithm.[15] We assess the impact of the shocks of external (exogenous) variables on inflation and on inflation expectations. We include the complete set of impulse responses in the Appendix. In addition, using our estimates, we decompose the series of inflation into the possible shocks that we have in our model.[16]

In robustness exercises, we include global shipping costs as an additional exogenous regressor, control for a measure of the output gap, consider alternative lag structures and ordering in the B-VAR, and consider an alternative definition of the relevant commodity price index.

4 Data

Our country-specific data comes from national sources and is compiled by Haver Analytics. The commodity price data is taken from the IMF's primary commodity price statistics.[17] In the specifications controlling for shipping costs, we use the Baltic Dry Index extracted from Bloomberg.[18] We use monthly data starting in most cases in January 2005 and ending in October 2022. The exact sample of each country is determined by the availability of data on 12-month ahead inflation expectations and on, where relevant, our measure of the output gap.

Table 1 provides some basic descriptive statistics of the data. For our sample, the commodity fuel prices grew, on average, 14 percent per year and were highly volatile, reaching a maximum of 169% in October 2021 as the world headed out from the COVID-19 pandemic lockdowns.

For our sample, inflation in the eight Latin-American and Caribbean countries explored was relatively low, averaging 4.3% across countries. The highest value was 14.5% in the Dominican Republic in September in 2008. 12-month inflation expectations were well anchored in most places averaging 4.1% across countries. The nominal exchange rate depreciation on average was 2.8%, but very volatile reaching yearly increases exceeding 60% in the cases of Colombia and Mexico.

[14] In theory, in a Bayesian framework, we would have to compute the posterior distribution of C, however, because of the Cholesky identification assumed exactly identifies C, it is possible to estimate draws from the posterior of C directly from draws from the posterior distribution of Σ. For a discussion of estimation details of Bayesian VARS see Ciccarelli and Rebucci (2003).

[15] We discard the first 1,000 iterations.

[16] Methodological details on these computations can be found in Kilian and Zhou (2022).

[17] See https://www.imf.org/en/Research/commodity-prices.

[18] The Baltic Dry Index is a daily measure reported by the Baltic Exchange in London and provides a benchmark for the price of moving the major raw materials by sea.

Tab. 1. Descriptive Statistics

		Sample	Obs.	Mean	St.Dev.	Min.	Max.
Global variables							
	Δ fuel	2005m1-2022m10	214	14.0	43.0	-60.8	168.8
	Δ Dry baltic	2005m1-2022m10	214	20.4	87.2	-93.0	443.6
Brasil							
	π	2005m1-2022m10	214	5.8	2.2	1.9	12.1
	Δ NER	2005m1-2022m10	214	5.0	19.3	-25.5	62.8
	12-month π^E	2005m1-2022m10	214	5.1	1.2	2.3	8.0
	Output gap	2005m1-2022m8	212	-0.4	3.8	-16.9	7.6
Chile							
	π	2005m1-2022m10	214	3.8	2.6	-2.3	14.1
	Δ NER	2005m1-2022m10	214	2.6	11.7	-24.8	34.4
	12-month π^E	2005m1-2022m10	214	3.3	0.9	2.0	7.3
	Output gap	2005m1-2022m8	212	-0.1	2.7	-13.4	7.6
Colombia							
	π	2005m1-2022m10	214	4.3	2.0	1.5	12.2
	Δ NER	2005m1-2022m10	214	3.5	14.4	-25.5	61.6
	12-month π^E	2005m1-2022m10	214	3.9	0.8	2.7	7.4
	Output gap	2005m1-2022m8	212	-0.1	3.1	-21.8	8.5
Costa Rica							
	π	2009m1-2022m10	166	3.5	2.9	-1.2	13.5
	Δ NER	2009m1-2022m10	166	1.7	5.5	-13.7	15.7
	12-month π^E	2009m1-2022m10	166	3.0	1.2	0.7	6.4
	Output gap	2009m1-2022m8	164	0.1	3.4	-13.0	9.7
Dominican Rep.							
	π	2008m1-2022m10	178	4.7	3.3	-1.6	14.6
	Δ NER	2008m1-2022m10	178	3.5	3.3	-6.9	14.8
	12-month π^E	2008m1-2022m10	178	5.2	1.8	2.4	11.6
	Output gap	2008m1-2022m8	NA	NA	NA	NA	NA
Mexico							
	π	2005m1-2022m10	214	4.3	1.3	2.1	8.7
	Δ NER	2005m1-2022m10	214	3.5	14.4	-25.5	61.6
	12-month π^E	2005m1-2022m10	214	4.2	1.1	2.2	8.5
	Output gap	2005m1-2022m7	211	-0.4	3.0	-23.5	3.3
Paraguay							
	π	2006m4-2022m10	199	5.1	3.0	0.5	13.5
	Δ NER	2006m4-2022m10	199	1.3	10.6	-23.2	27.1
	12-month π^E	2006m4-2022m10	199	5.5	1.8	2.5	11.0
	Output gap	2006m4-2022m8	197	-0.1	5.7	-21.0	19.0
Peru							
	π	2005m1-2022m10	214	3.1	1.7	-0.1	8.8
	Δ NER	2005m1-2022m10	214	0.9	6.4	-13.7	15.6
	12-month π^E	2005m1-2022m10	214	2.8	0.7	1.4	5.4
	Output gap	2005m1-2022m8	212	-0.3	6.7	-62.5	10.1

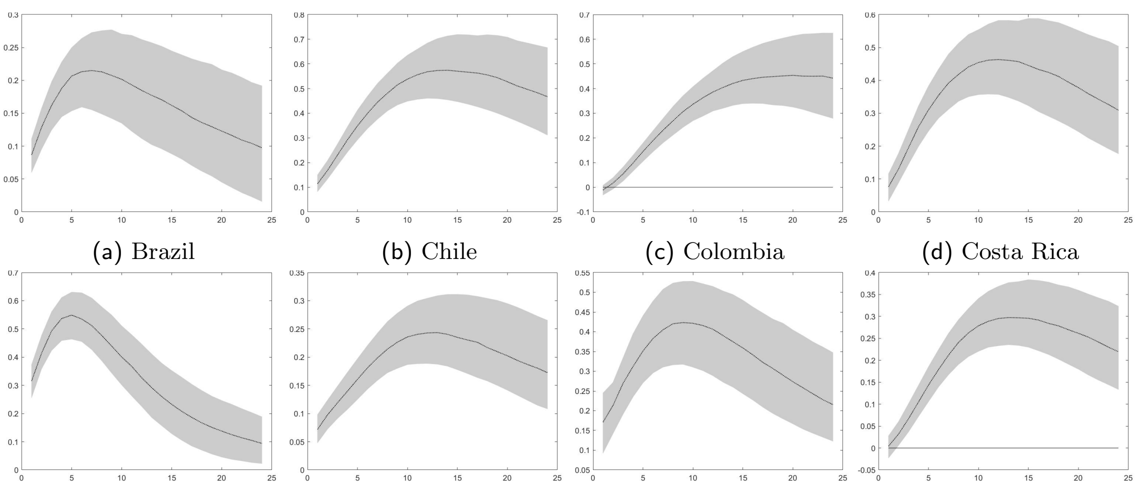
Source: Country-specific data comes from Haver Analytics. Fuel prices are from the IMF's commodity price database and the Dry Baltic index is from Bloomberg.
Note: Δ denotes a 12-month percentage variation. NER is the nominal exchange rate of the domestic currency against the US dollar. π is the 12-month CPI inflation rate.

5 Results

In our baseline exercise, to analyze the role played by oil shocks in determining inflation, we estimate the B-VAR for each of the eight countries and their corresponding impulse response functions and historical decomposition based on the estimated structural shocks. The complete set of impulse-response functions for the baseline is reported in Appendix A. Here we focus on a few impulse-response functions and the historical decomposition exercises.

Figure 1 plots the median impulse-response function simulated of the 12-month inflation rate to a one standard deviation shock to fuel commodities (14 p.p.) for each country. As usual in this literature, sixty-six percent confidence intervals are reported. In all cases, inflation responds significantly and rapidly to a shock in fuel prices. The largest impact after six months is reported in the Dominican Republic where inflation increases by 0.54 p.p. (this is equivalent to a response of 0.04 p.p. to a 1 p.p. shock). The lowest impact is estimated in Peru where it increases by only 0.18 p.p. after the shock (a 0.01 p.p. response to a 1 p.p. shock). The impact of the shock falls pretty rapidly in Brazil, the Dominican Republic, and Paraguay where the peak is estimated at months 7, 5, and 9, respectively. It is more persistent in Chile, Costa Rica, Mexico, and Peru, where it peaks at 14, 12, 13, and 13 months, respectively, and appears to be highly persistent in Colombia where it only curbs after 20 months. After 12 months, the response of inflation is highest in Chile (0.57 p.p.) and lowest in Brazil (0.19 p.p.).[19]

Fig. 1. Impulse-Response Function of Inflation to a Fuel-Price Shock



(a) Brazil (b) Chile (c) Colombia (d) Costa Rica

(e) Dominican Rep. (f) Mexico (g) Paraguay (h) Peru

Source: Authors' own calculations based on national sources and IMF commodity price data.
Note: Response of inflation to a one standard deviation shock to fuel commodity prices. The median value and 66% confidence intervals are reported.

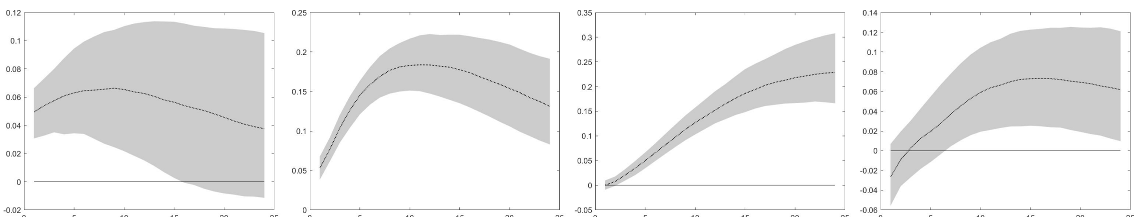
It is worth noting that in all of these countries, there exists some type of fiscally supported mechanism to reduce the impact of global fuel prices on domestic fuel ones. Hence, most likely

[19] These numbers are equivalent to a 0.04 p.p. and 0.01 p.p. response, respectively, to a 1 p.p. shock in oil prices, and lie within what has been found in previous literature.

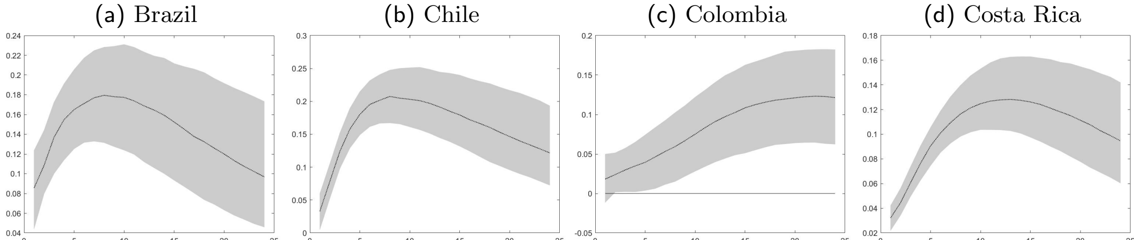
the transmission channel may be directly through the increase in the cost of imported goods and services, or through other dynamics not specified explicitly in the model such as increased demand associated with higher negotiated wages or subsidies as in Blanchard and Gali (2007). The size of the impact and the persistence and dynamics of the transmission may be related to the idiosyncratic functioning of each gasoline price smoothing mechanism.

A key feature in inflation-targeting regimes lies in how inflation expectations adjust following shocks. Figure 2 plots the response of 12-month ahead inflation expectations to the one standard deviation fuel-price shock. The impulse responses follow a similar pattern to those of inflation, they remain significant, though the estimated levels are nearly half of those estimated for inflation. After 12 months, the response of inflation expectations to a one standard deviation fuel-price shock ranges from 0.06 p.p. in Brazil to 0.2 p.p. in Mexico. As above, the response of inflation expectations fades rapidly in Brazil and the Dominican Republic and is highly persistent in Colombia.[20] The case of Paraguay calls our attention since inflation expectations seem to follow a different pattern than that of inflation.

Fig. 2. Impulse-Response Function of Inflation Expectations to a Fuel-Price Shock



(a) Brazil (b) Chile (c) Colombia (d) Costa Rica



(e) Dominican Rep. (f) Mexico (g) Paraguay (h) Peru

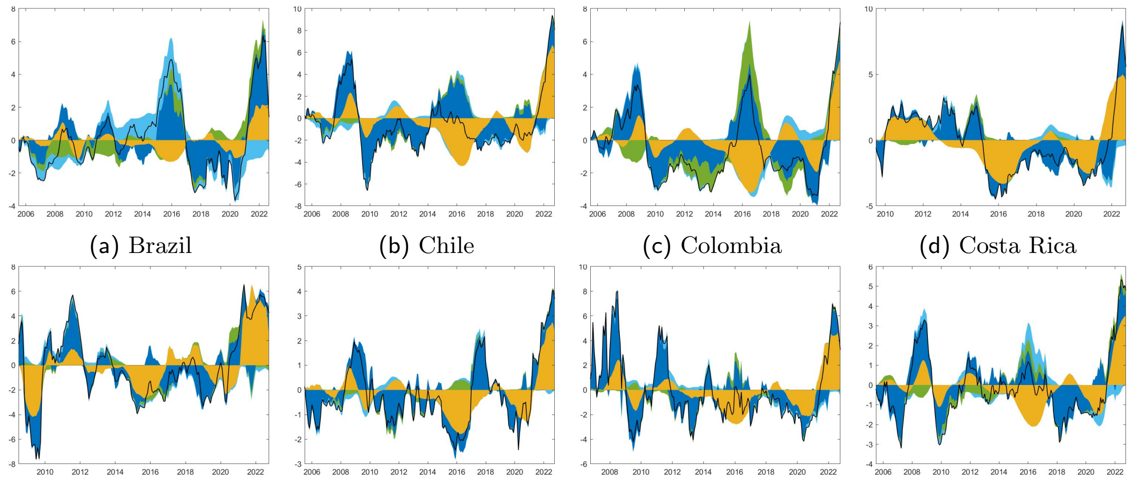
Source: Authors' own calculations based on national sources and IMF commodity price data.
Note: Response of inflation expectations to a one standard deviation shock to fuel commodity prices. The median value and 66% confidence intervals are reported.

To understand the main drivers of inflation throughout our sample we compute the historical decomposition of the path of the stochastic component of inflation with respect to all estimated structural shocks. These are reported in Figure 3. Except for Brazil, fuel price shocks explain more than 70% of the exogenous variation of inflation estimated by our models in the last quarter of the sample. In the cases of the Dominican Republic and Paraguay it explains more than 90% of the variation. Overall these findings suggest that the external dynamics in fuel prices have been the main driver of CPI inflation in Latin America and the Caribbean.

[20] This finding is consistent with Conflitti and Cristadoro (2018) and Wong (2015).

Figure 4 shows the historical decomposition of inflation expectations. In line with Figure 3 it shows the key role placed by fuel price shocks in shaping inflation expectations, a key signal for policymakers about the need to communicate to the public their views about the nature of fuel-price shocks, for example about the perceived persistence or not of key market shocks.

Fig. 3. Historical Decomposition of Inflation



(a) Brazil (b) Chile (c) Colombia (d) Costa Rica

(e) Dominican Rep. (f) Mexico (g) Paraguay (h) Peru

Source: Authors' own calculations based on national sources and IMF commodity price data.
Note: The yellow area corresponds to the shocks to the fuel price, the blue area to inflation shocks, the green area to the nominal exchange rate shocks, and the light blue area to the inflation expectation shocks.

6 Robustness checks

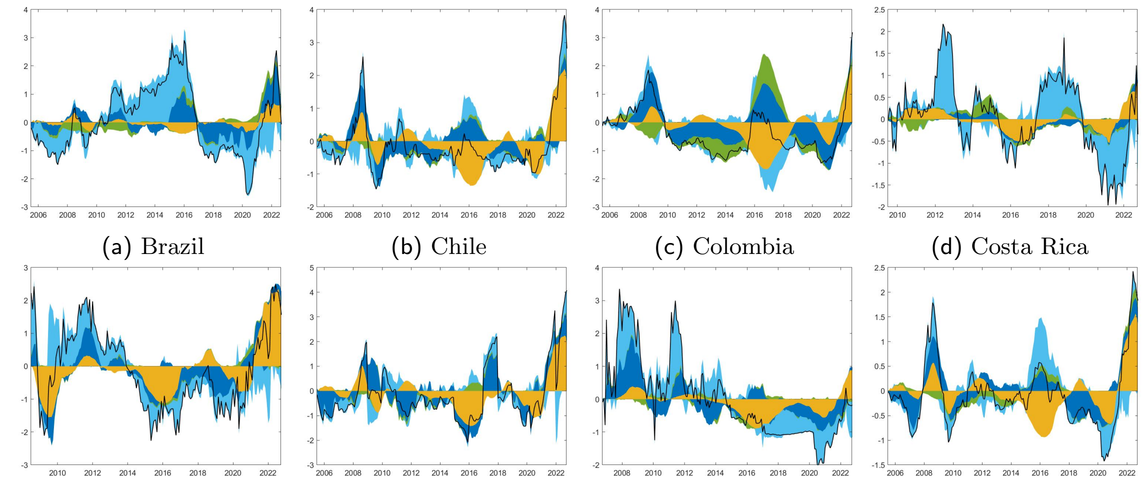
In order to test the robustness of our baseline results, we perform a battery of additional tests to see how the main result regarding the impact of global fuel price shocks affects inflation in Latin America and the Caribbean. First, we control for an additional global shock that has been highlighted by recent literature: the increase in global shipping costs, closely linked with global supply side disturbances. Next, we control for the output gap, a common measure used in inflation models, to capture aggregate demand pressure affecting inflation. We also alter the main specification in terms of lag structure and order of the variables.

6.1 Controlling for global shipping costs

In our first robustness exercise, we include a measure of global shipping costs as an exogenous determinant of inflation. Recent literature has shown the importance of global shipping costs on inflation, particularly following notorious supply-side restrictions prevailing globally since the COVID-19 pandemic and the invasion of Russia to Ukraine.[21]

[21] See for example Carrière-Swallow et al. (2022) and Guilloux-Nefussi and Rusticelli (2021).

Fig. 4. Historical Decomposition of Inflation Expectations



(a) Brazil (b) Chile (c) Colombia (d) Costa Rica

(e) Dominican Rep. (f) Mexico (g) Paraguay (h) Peru

Source: Authors' own calculations based on national sources and IMF commodity price data.
Note: The yellow area corresponds to the shocks to the fuel price, the blue area to inflation shocks, the green area to the nominal exchange rate shocks, and the light blue area to the inflation expectation shocks.

In order to incorporate shipping costs as an exogenous variable, we redefine the baseline B-VAR model as follows. Let $y_t = [\Delta fuel_t,\ \Delta shcost_t,\ \pi_t,\ \Delta NER_t,\ \pi_t^E]'$, where the new variable $\Delta shcost_t$ is the 12-month change in the Baltic Dry Index, a commonly used proxy of shipping costs. The rest of the variables remain as previously defined.

The B-VAR model now has an exogenous block of the global variables $\Delta fuel_t$ and $\Delta shcost_t$. We ensure exogeneity by setting priors of zero for the relevant parameters in the model and allowing for very little adjustment during the Bayesian estimation. The typical A_j matrix in Equation (1), for each j between 1 and p now has the following form:

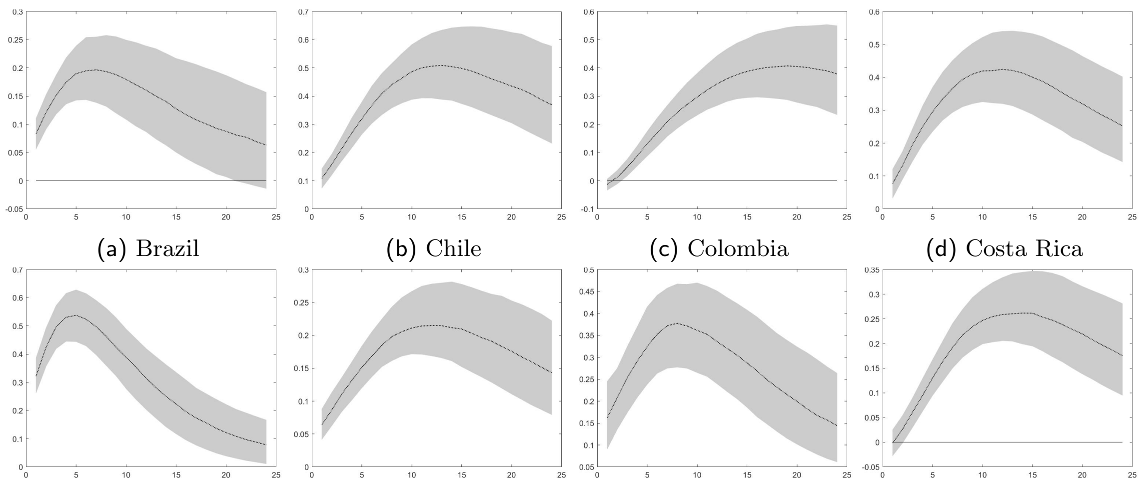
$$A_j = \begin{pmatrix} a_{11}^j & a_{12}^j & 0 & 0 & 0 \\ a_{21}^j & a_{22}^j & 0 & 0 & 0 \\ a_{31}^j & a_{32}^j & a_{33}^j & a_{34}^j & a_{35}^j \\ a_{41}^j & a_{42}^j & a_{43}^j & a_{44}^j & a_{45}^j \\ a_{51}^j & a_{52}^j & a_{53}^j & a_{54}^j & a_{55}^j \end{pmatrix}. \tag{5}$$

As above, we work with a Cholesky factorization, which means that the order of the variable matter. Regarding the global components, we allow global oil price shocks to affect shipping costs contemporaneously, but not the other way around.

Figure 5 plots the impulse response function of inflation to the global fuel price shock controlling for shipping costs as described. The results resemble closely those of Figure 1, suggesting that in this sample of countries, the impact of fuel price commodities dominates that of global shipping costs.

An interesting result of this exercise is to plot the impact of changes in global shipping costs on inflation. Figure 6 plots the impulse-response functions of a shock to one standard deviation shock to shipping costs (48 p.p.) on inflation. The impact of the shipping-costs shock on inflation is significant in most cases and has a dynamic similar to that of the fuel-price shocks regarding the persistence in each country. Despite the significance of the impulse responses, in economic terms, shipping-cost shocks have not been as relevant in Latin America and the Caribbean, compared to fuel-price shocks, as Figure 7 shows.

Fig. 5. Impulse-Response Function of Inflation to a Fuel-Price Shock Controlling for Shipping Costs



(a) Brazil (b) Chile (c) Colombia (d) Costa Rica

(e) Dominican Rep. (f) Mexico (g) Paraguay (h) Peru

Source: Authors' own calculations based on national sources and IMF commodity price data.
Note: Response of inflation to a one standard deviation shock to fuel commodity prices. The median value and 66% confidence intervals are reported.

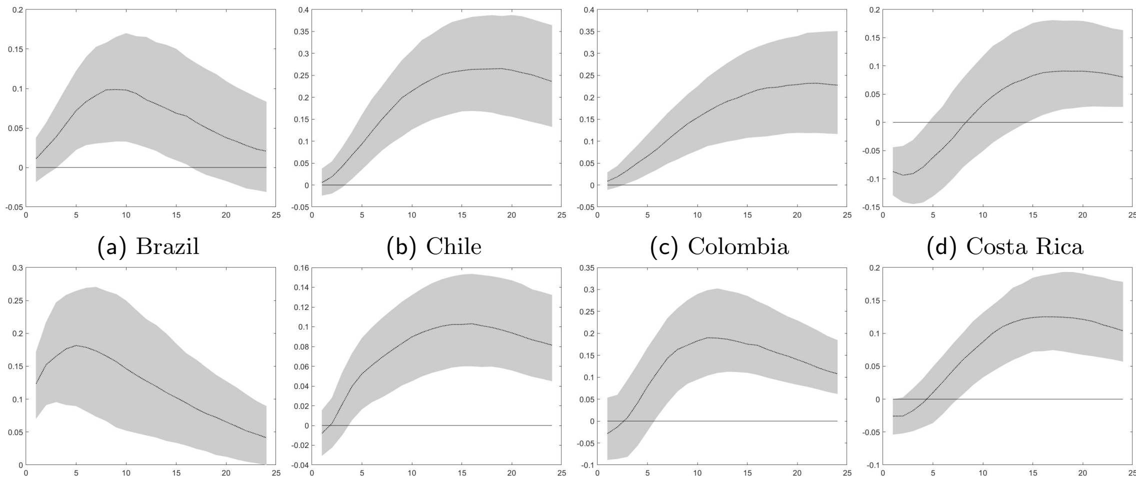
Figure 7 presents the historical decomposition of inflation in the setup that includes shipping costs (orange area). Compared to the fuel-price shocks (yellow area), the impact has been negligible, particularly in the last few years of the sample which is characterized by the COVID-19 pandemic and the war of Russia in Ukraine.

6.2 Controlling for the output gap

A key variable usually included in the theoretical modeling of inflation is the output gap. One of the main difficulties in including it in practical exercises is that since it is not observable, it needs to be estimated.[22] A typical proxy of the output gap results from using a times series filter to extract a trend and a cyclical component from a real output time series. Here we measure the output gap by applying a one-sided Hodrick-Prescott filter with λ equal to 129,600, to country-specific monthly data of economic activity.[23] In this exercise, the sample for estimations is determined by the availability of the monthly-economic activity index. As noted in Table 1 this data is not available for the Dominican Republic.

[22] For a discussion on the perils of estimating output gaps see Barbarino et al. (2020).
[23] The choice of a one-sided filter is used to avoid that the filter anticipates highly unexpected phenomena such as the COVID-19 pandemic.

Fig. 6. Impulse-Response Function of Inflation to a Shipping-Costs Shock



(a) Brazil (b) Chile (c) Colombia (d) Costa Rica

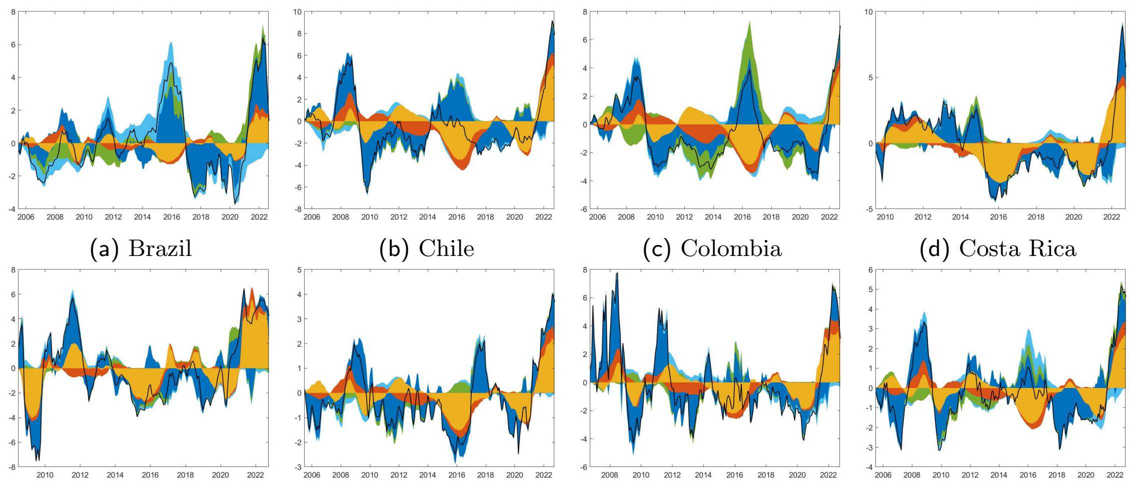
(e) Dominican Rep. (f) Mexico (g) Paraguay (h) Peru

Source: Authors' own calculations based on national sources and IMF commodity price data.
Note: Response of inflation to a one standard deviation shock to fuel commodity prices. The median value and 66% confidence intervals are reported.

Figures 8 and 9 plot the impulse response functions of inflation to a fuel price shock, and the historical decomposition of inflation, including the output gap measure, respectively. Notably, Figure 8 shows very few fluctuations with respect to the baseline model confirming its robustness.

The historical decompositions plotted in Figure 9 show that the prevailing factor explaining inflation lies in the exogenous fuel commodity price shocks, while the output gap has played a very small role, particularly in the last period of our sample. Probably this is the consequence of estimation problems in the estimation of the gap itself.

Fig. 7. Historical Decomposition of Inflation, Controlling for Shipping Costs



(a) Brazil (b) Chile (c) Colombia (d) Costa Rica

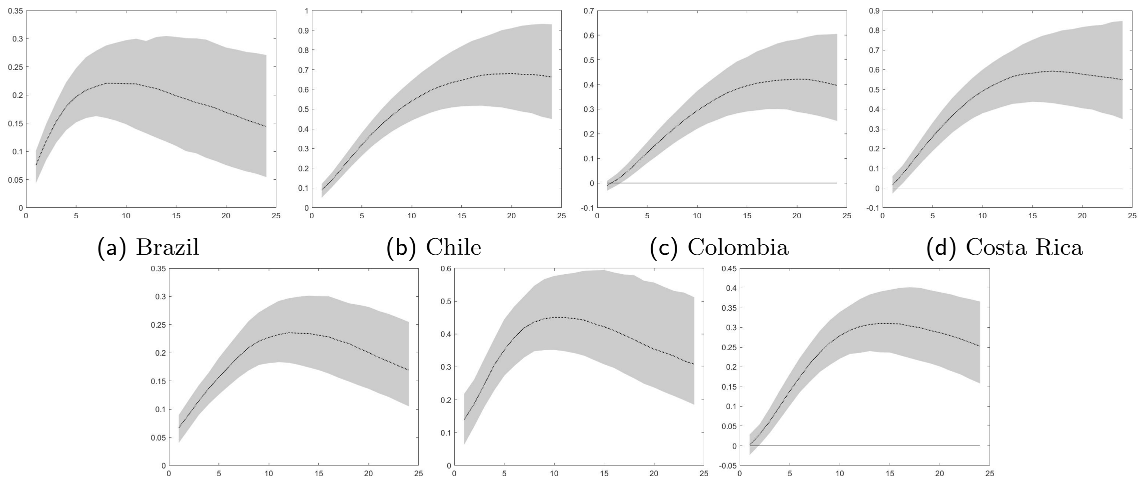
(e) Dominican Rep. (f) Mexico (g) Paraguay (h) Peru

Source: Authors' own calculations based on national sources and IMF commodity price data.
Note: The yellow area corresponds to the shocks to the fuel price, the blue area to inflation shocks, the orange area to shipping costs, the green area to the nominal exchange rate shocks, and the light blue area to the inflation expectation shocks.

6.3 Alternative specifications

A final set of robustness exercises consist is changing elements of the specification of the B-VAR model, namely the lag length and the ordering of the domestic variables. To test the robustness of our baseline we shorten the lag length to 3-month structure, compared with our more conservative 6-month one, and alter the order of the country-specific and endogenous variables of the model. In this last exercise, we switch the nominal exchange rate depreciation and the 12-month ahead inflation expectations variable, to allow the former to be the most endogenous (contemporaneously) in the system. The results reported in Figures 10 and 11 reveal very few changes compared to the baseline.

Fig. 8. Impulse-Response Function of Inflation to a Fuel-Price Shock Controlling for the Output Gap



(a) Brazil (b) Chile (c) Colombia (d) Costa Rica

(e) Mexico (f) Paraguay (g) Peru

Source: Authors' own calculations based on national sources and IMF commodity price data.
Note: Response of inflation to a one standard deviation shock to fuel commodity prices. The median value and 66% confidence intervals are reported.

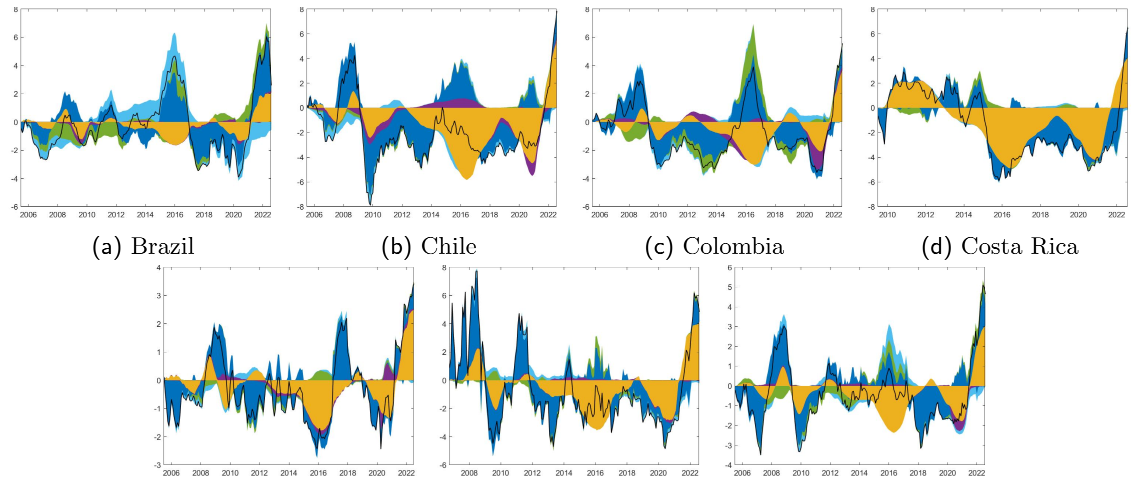
7 Conclusion

Fuel-commodity price shocks play a significant role in explaining headline inflation and inflation expectation dynamics in Latin American countries that follow inflation-targeting frameworks in their conduction of monetary policy. Using Bayesian vector auto-regressive models estimated for eight countries, we find that a one standard deviation shock to fuel prices can increase headline inflation between 0.19 and 0.57 percentage points, and inflation expectations between 0.06 and 0.20 percentage points after 12 months.

These results are relevant in terms of informing the response of monetary policy to fuel-commodity price shocks. Despite being external shocks in many cases of a transitory nature, the fact that they can affect inflation expectations, with a risk of de-anchoring them, calls for a strong policy response by central banks, given that guiding expectations is central to the inflation targeting toolkit.

This paper also highlights the relevance of foreign developments such as the COVID-19 pandemic and the invasion of Russia into Ukraine in explaining the outburst in inflation dynamics experienced by Latin America (and the world in general) since the end of 2021. In the cases studied here, the oil price shock explained more than 60% of the inflation during that period.

Fig. 9. Historical Decomposition of Inflation, Controlling for the Output Gap

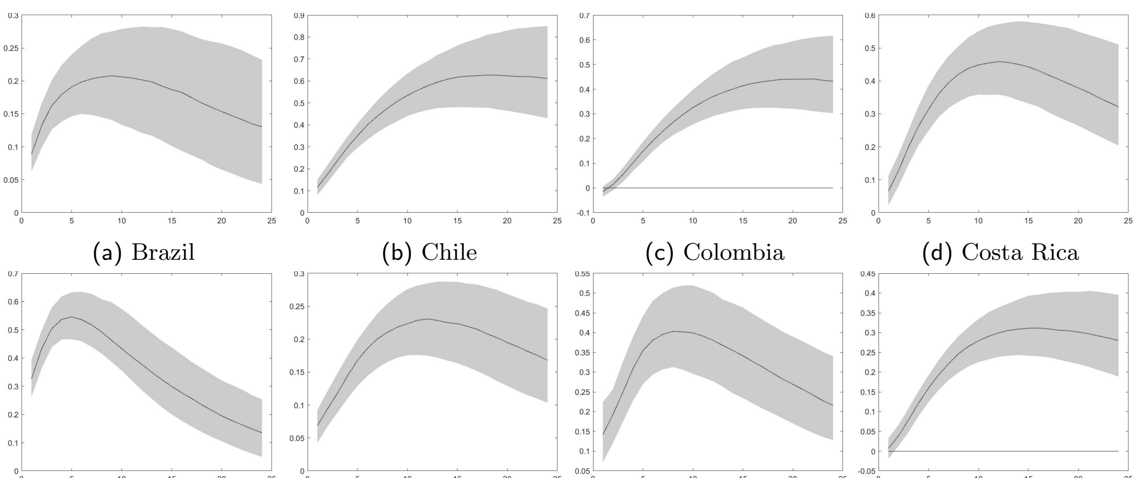


(a) Brazil (b) Chile (c) Colombia (d) Costa Rica

(e) Mexico (f) Paraguay (g) Peru

Source: Authors' own calculations based on national sources and IMF commodity price data.
Note: The yellow area corresponds to the shocks to the fuel price, the blue area to inflation shocks, the purple area to the output gap, the green area to the nominal exchange rate shocks, and the light blue area to the inflation expectation shocks.

Fig. 10. Impulse-Response Function of Inflation to a Fuel-Price Shock, Alternative Lag Structure

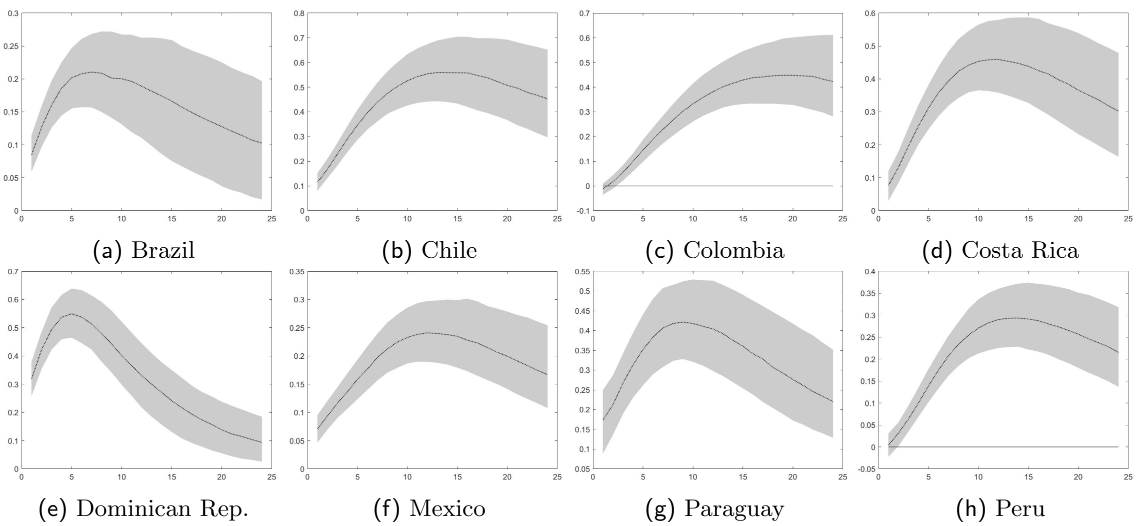


(a) Brazil (b) Chile (c) Colombia (d) Costa Rica

(e) Dominican Rep. (f) Mexico (g) Paraguay (h) Peru

Source: Authors' own calculations based on national sources and IMF commodity price data.
Note: Response of inflation to a one standard deviation shock to fuel commodity prices. The median value and 66% confidence intervals are reported.

Fig. 11. Impulse-Response Function of Inflation to a Fuel-Price Shock, Alternative Variable Order



(a) Brazil (b) Chile (c) Colombia (d) Costa Rica

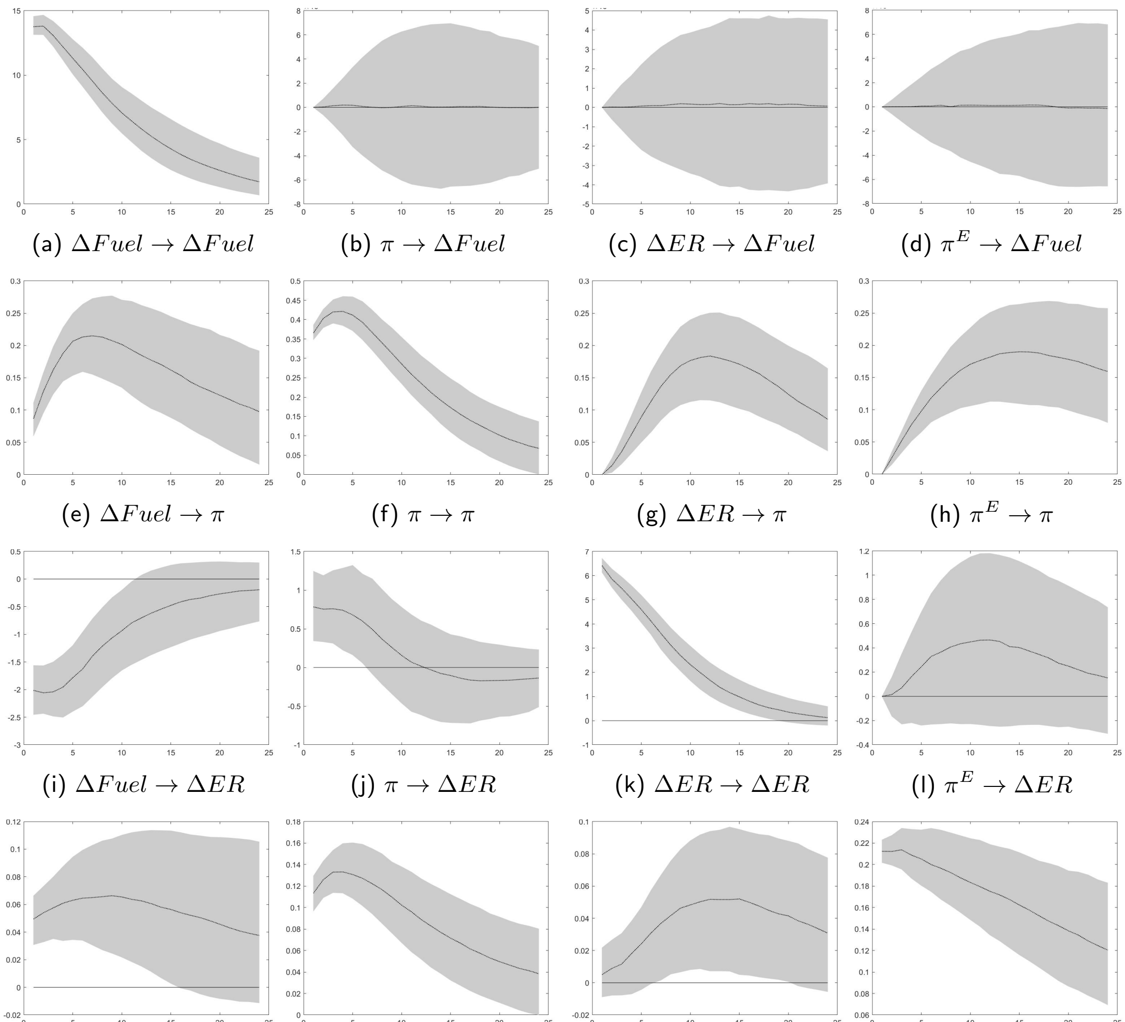
(e) Dominican Rep. (f) Mexico (g) Paraguay (h) Peru

Source: Authors' own calculations based on national sources and IMF commodity price data.
Note: Response of inflation to a one standard deviation shock to fuel commodity prices. The median value and 66% confidence intervals are reported.

Appendices

A Impulse Responses of Baseline Model by Country

Fig. A.1. Brazil: Impulse-Response Functions, Baseline Model



(a) $\Delta Fuel \rightarrow \Delta Fuel$ (b) $\pi \rightarrow \Delta Fuel$ (c) $\Delta ER \rightarrow \Delta Fuel$ (d) $\pi^E \rightarrow \Delta Fuel$

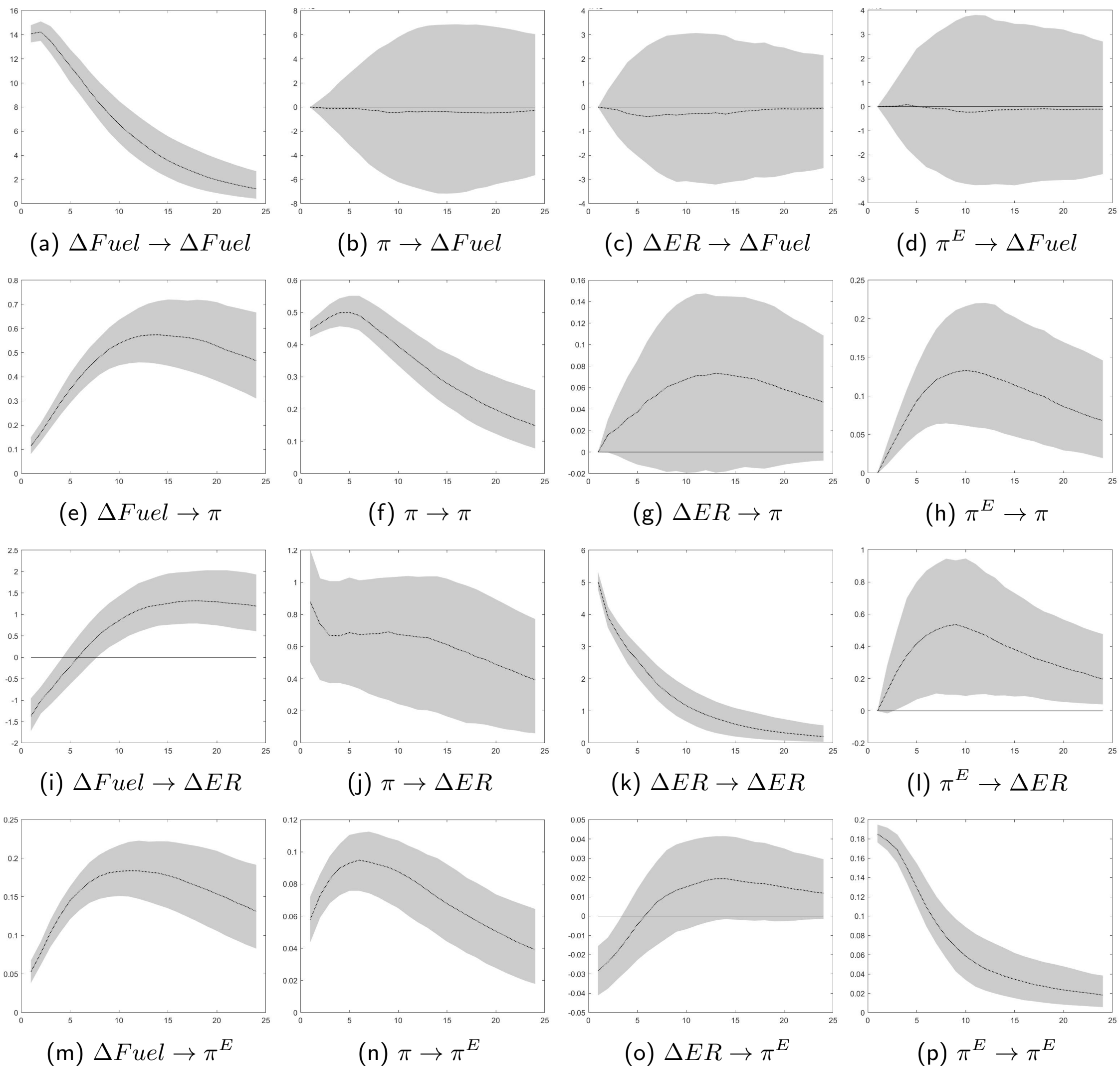
(e) $\Delta Fuel \rightarrow \pi$ (f) $\pi \rightarrow \pi$ (g) $\Delta ER \rightarrow \pi$ (h) $\pi^E \rightarrow \pi$

(i) $\Delta Fuel \rightarrow \Delta ER$ (j) $\pi \rightarrow \Delta ER$ (k) $\Delta ER \rightarrow \Delta ER$ (l) $\pi^E \rightarrow \Delta ER$

(m) $\Delta Fuel \rightarrow \pi^E$ (n) $\pi \rightarrow \pi^E$ (o) $\Delta ER \rightarrow \pi^E$ (p) $\pi^E \rightarrow \pi^E$

Source: Authors' own calculations based on national sources and IMF commodity price data.
Note: Response to a one standard deviation shock of the relevant variable. The median value and 66% confidence intervals are reported.

Fig. A.2. Chile: Impulse-Response Functions, Baseline Model



(a) $\Delta Fuel \rightarrow \Delta Fuel$ (b) $\pi \rightarrow \Delta Fuel$ (c) $\Delta ER \rightarrow \Delta Fuel$ (d) $\pi^E \rightarrow \Delta Fuel$

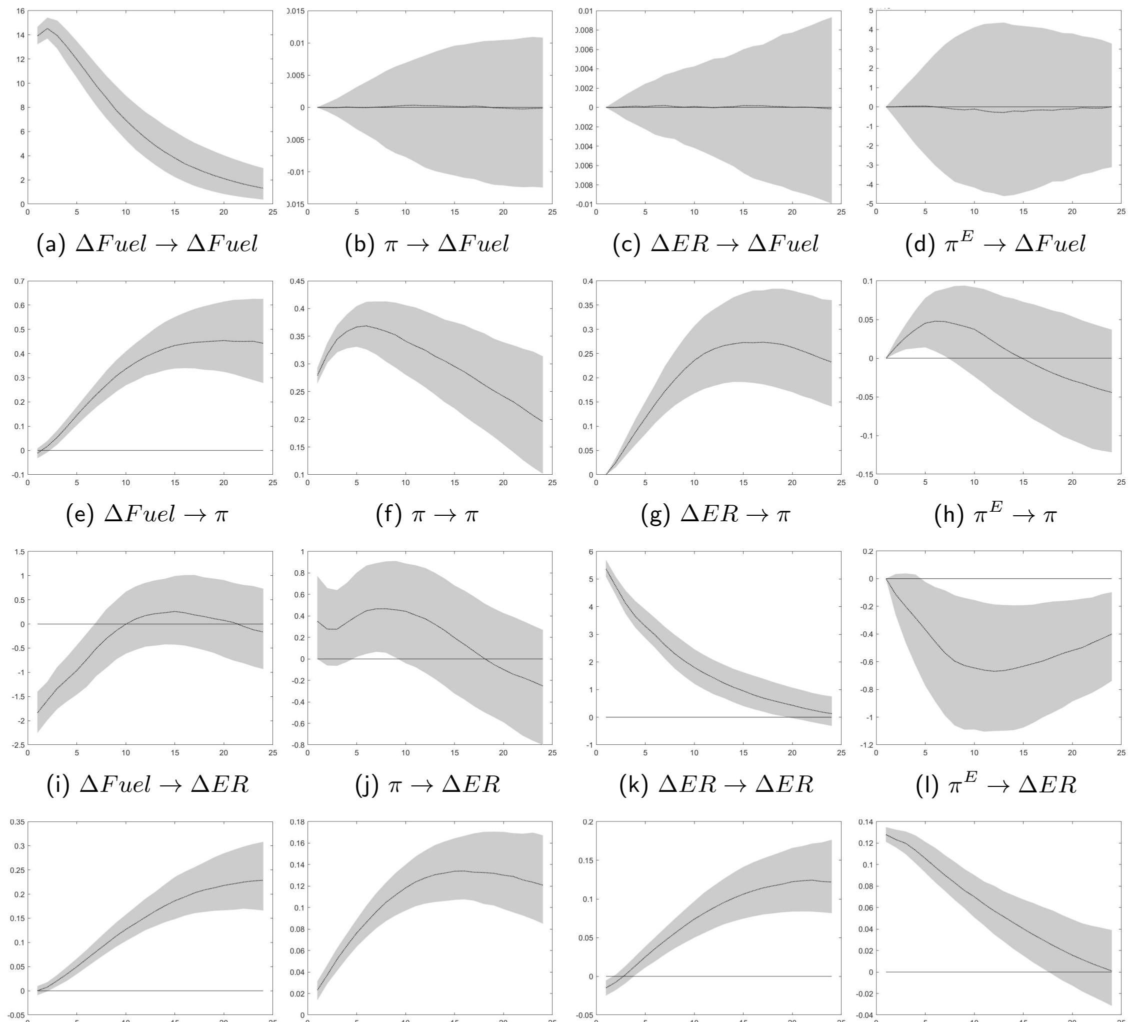
(e) $\Delta Fuel \rightarrow \pi$ (f) $\pi \rightarrow \pi$ (g) $\Delta ER \rightarrow \pi$ (h) $\pi^E \rightarrow \pi$

(i) $\Delta Fuel \rightarrow \Delta ER$ (j) $\pi \rightarrow \Delta ER$ (k) $\Delta ER \rightarrow \Delta ER$ (l) $\pi^E \rightarrow \Delta ER$

(m) $\Delta Fuel \rightarrow \pi^E$ (n) $\pi \rightarrow \pi^E$ (o) $\Delta ER \rightarrow \pi^E$ (p) $\pi^E \rightarrow \pi^E$

Source: Authors' own calculations based on national sources and IMF commodity price data.
Note: Response to a one standard deviation shock of the relevant variable. The median value and 66% confidence intervals are reported.

Fig. A.3. Colombia: Impulse-Response Functions, Baseline Model



(a) $\Delta Fuel \rightarrow \Delta Fuel$ (b) $\pi \rightarrow \Delta Fuel$ (c) $\Delta ER \rightarrow \Delta Fuel$ (d) $\pi^E \rightarrow \Delta Fuel$

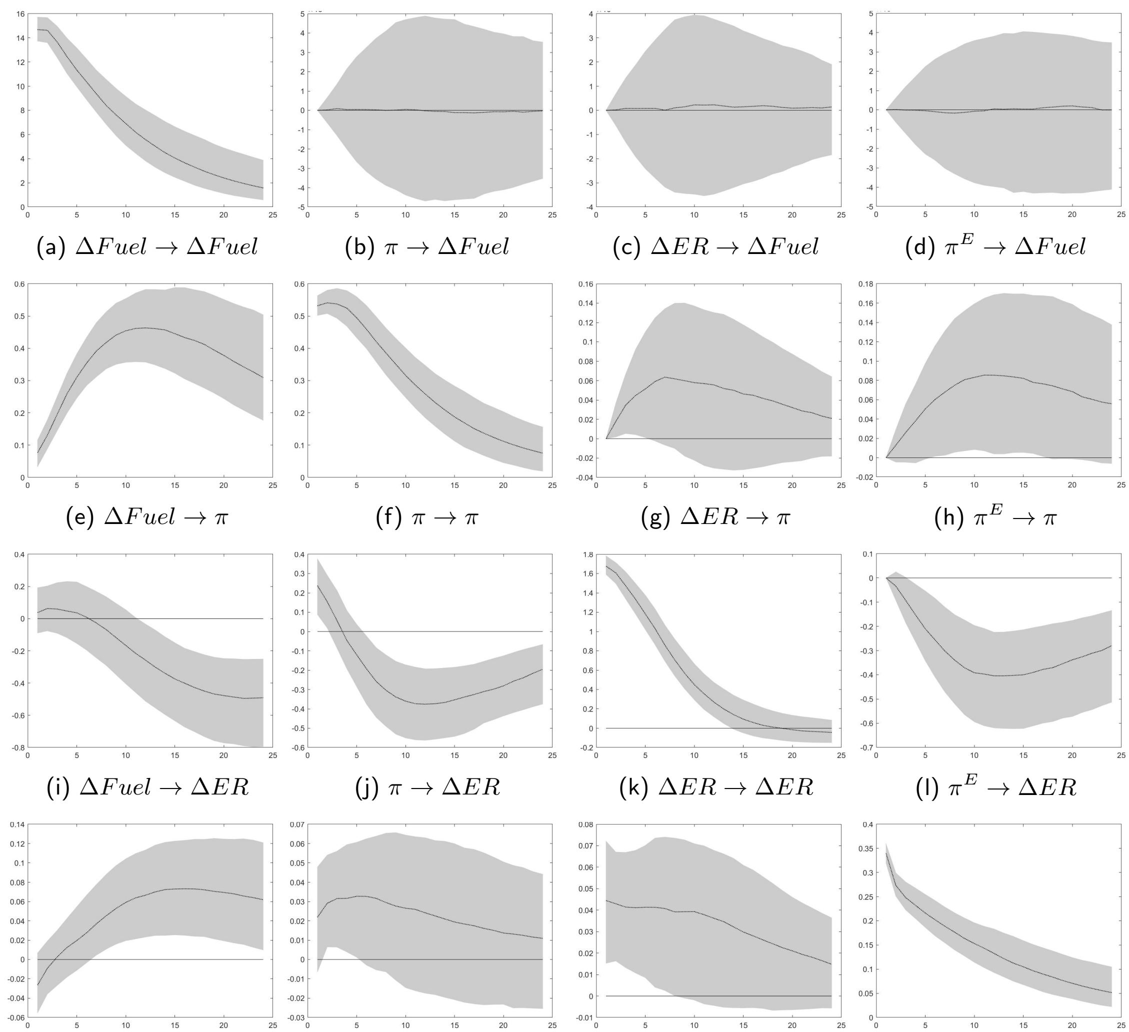
(e) $\Delta Fuel \rightarrow \pi$ (f) $\pi \rightarrow \pi$ (g) $\Delta ER \rightarrow \pi$ (h) $\pi^E \rightarrow \pi$

(i) $\Delta Fuel \rightarrow \Delta ER$ (j) $\pi \rightarrow \Delta ER$ (k) $\Delta ER \rightarrow \Delta ER$ (l) $\pi^E \rightarrow \Delta ER$

(m) $\Delta Fuel \rightarrow \pi^E$ (n) $\pi \rightarrow \pi^E$ (o) $\Delta ER \rightarrow \pi^E$ (p) $\pi^E \rightarrow \pi^E$

Source: Authors' own calculations based on national sources and IMF commodity price data.
Note: Response to a one standard deviation shock of the relevant variable. The median value and 66% confidence intervals are reported.

Fig. A.4. Costa Rica: Impulse-Response Functions, Baseline Model



(a) $\Delta Fuel \rightarrow \Delta Fuel$ (b) $\pi \rightarrow \Delta Fuel$ (c) $\Delta ER \rightarrow \Delta Fuel$ (d) $\pi^E \rightarrow \Delta Fuel$

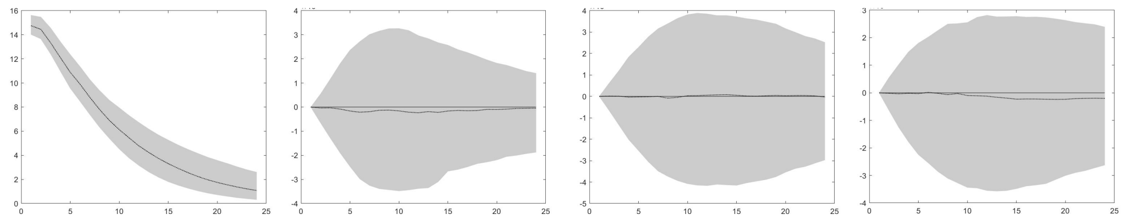
(e) $\Delta Fuel \rightarrow \pi$ (f) $\pi \rightarrow \pi$ (g) $\Delta ER \rightarrow \pi$ (h) $\pi^E \rightarrow \pi$

(i) $\Delta Fuel \rightarrow \Delta ER$ (j) $\pi \rightarrow \Delta ER$ (k) $\Delta ER \rightarrow \Delta ER$ (l) $\pi^E \rightarrow \Delta ER$

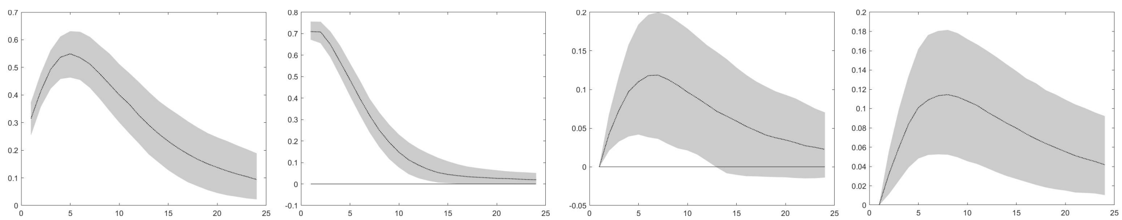
(m) $\Delta Fuel \rightarrow \pi^E$ (n) $\pi \rightarrow \pi^E$ (o) $\Delta ER \rightarrow \pi^E$ (p) $\pi^E \rightarrow \pi^E$

Source: Authors' own calculations based on national sources and IMF commodity price data.
Note: Response to a one standard deviation shock of the relevant variable. The median value and 66% confidence intervals are reported.

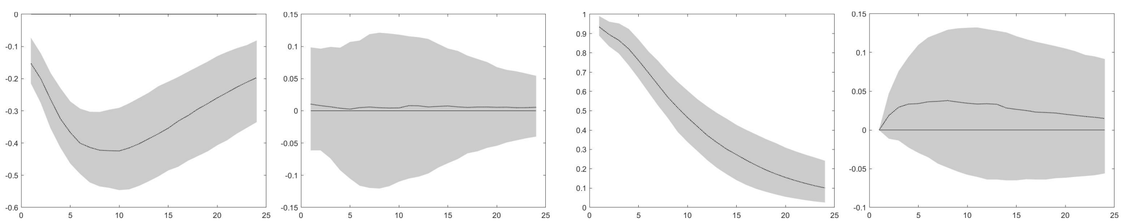
Fig. A.5. Dominican Republic: Impulse-Response Functions, Baseline Model



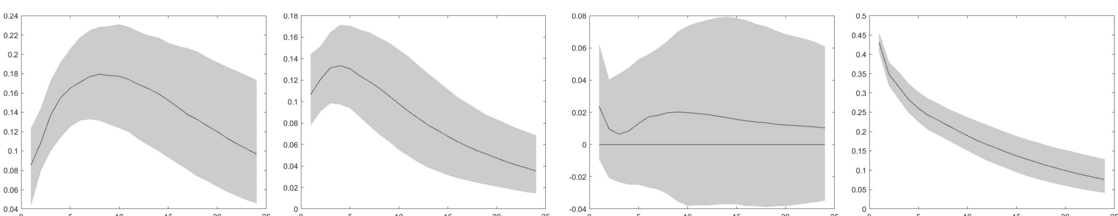
(a) $\Delta Fuel \rightarrow \Delta Fuel$ (b) $\pi \rightarrow \Delta Fuel$ (c) $\Delta ER \rightarrow \Delta Fuel$ (d) $\pi^E \rightarrow \Delta Fuel$



(e) $\Delta Fuel \rightarrow \pi$ (f) $\pi \rightarrow \pi$ (g) $\Delta ER \rightarrow \pi$ (h) $\pi^E \rightarrow \pi$



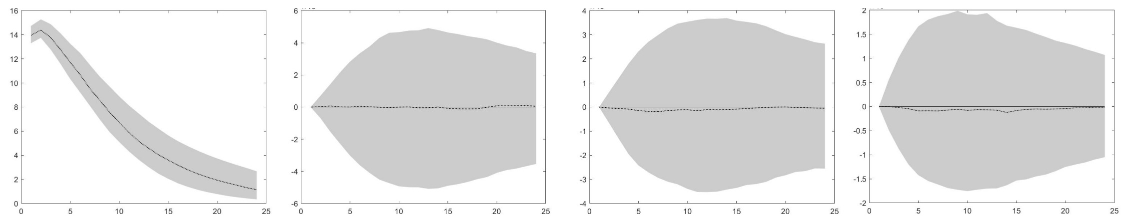
(i) $\Delta Fuel \rightarrow \Delta ER$ (j) $\pi \rightarrow \Delta ER$ (k) $\Delta ER \rightarrow \Delta ER$ (l) $\pi^E \rightarrow \Delta ER$



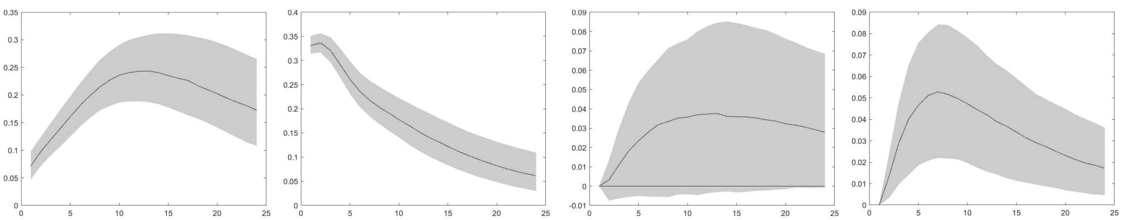
(m) $\Delta Fuel \rightarrow \pi^E$ (n) $\pi \rightarrow \pi^E$ (o) $\Delta ER \rightarrow \pi^E$ (p) $\pi^E \rightarrow \pi^E$

Source: Authors' own calculations based on national sources and IMF commodity price data.
Note: Response to a one standard deviation shock of the relevant variable. The median value and 66% confidence intervals are reported.

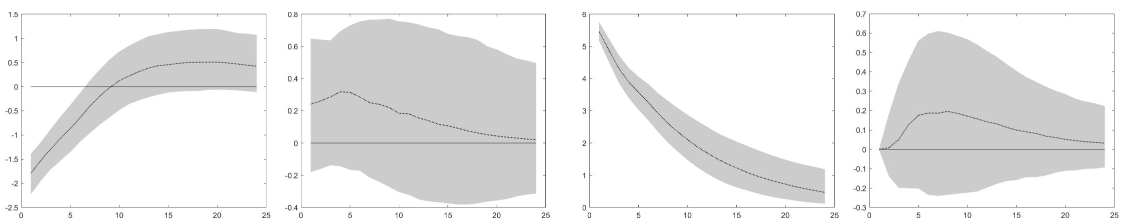
Fig. A.6. Mexico: Impulse-Response Functions, Baseline Model



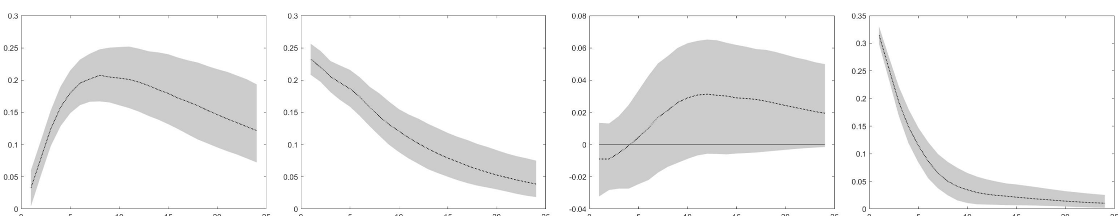
(a) $\Delta Fuel \rightarrow \Delta Fuel$ (b) $\pi \rightarrow \Delta Fuel$ (c) $\Delta ER \rightarrow \Delta Fuel$ (d) $\pi^E \rightarrow \Delta Fuel$



(e) $\Delta Fuel \rightarrow \pi$ (f) $\pi \rightarrow \pi$ (g) $\Delta ER \rightarrow \pi$ (h) $\pi^E \rightarrow \pi$



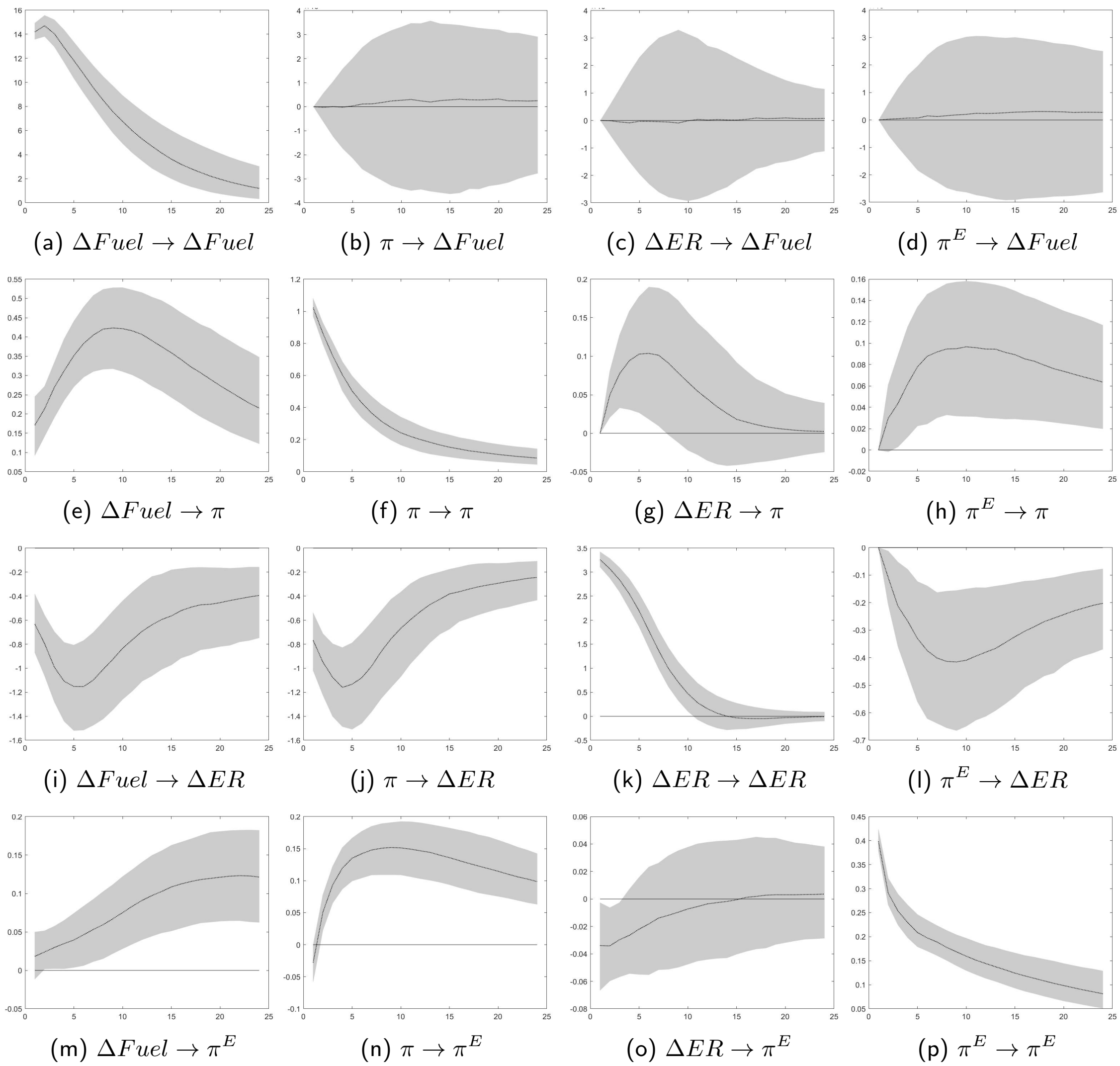
(i) $\Delta Fuel \rightarrow \Delta ER$ (j) $\pi \rightarrow \Delta ER$ (k) $\Delta ER \rightarrow \Delta ER$ (l) $\pi^E \rightarrow \Delta ER$



(m) $\Delta Fuel \rightarrow \pi^E$ (n) $\pi \rightarrow \pi^E$ (o) $\Delta ER \rightarrow \pi^E$ (p) $\pi^E \rightarrow \pi^E$

Source: Authors' own calculations based on national sources and IMF commodity price data.
Note: Response to a one standard deviation shock of the relevant variable. The median value and 66% confidence intervals are reported.

Fig. A.7. Paraguay: Impulse-Response Functions, Baseline Model



(a) $\Delta Fuel \rightarrow \Delta Fuel$ (b) $\pi \rightarrow \Delta Fuel$ (c) $\Delta ER \rightarrow \Delta Fuel$ (d) $\pi^E \rightarrow \Delta Fuel$

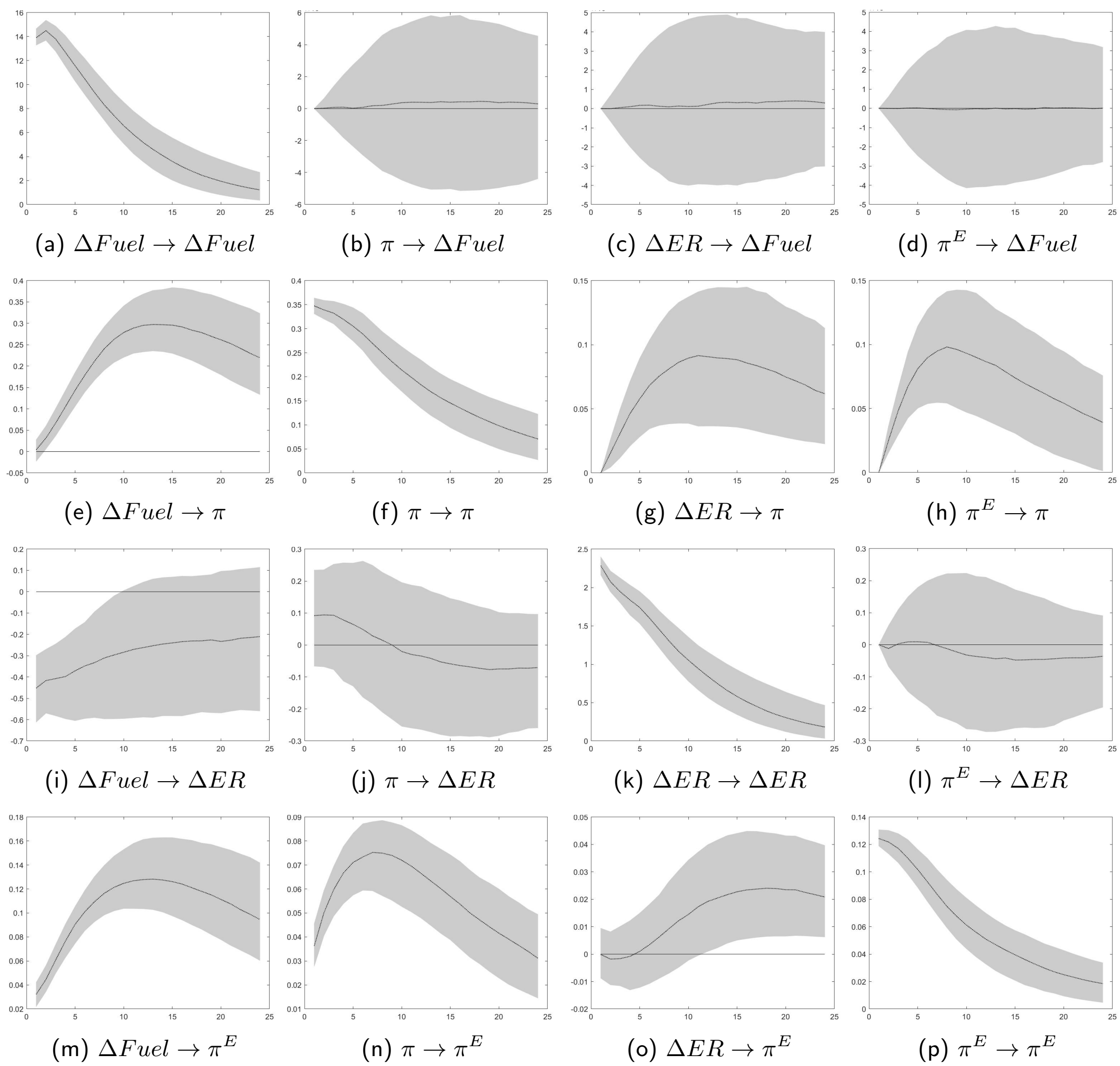
(e) $\Delta Fuel \rightarrow \pi$ (f) $\pi \rightarrow \pi$ (g) $\Delta ER \rightarrow \pi$ (h) $\pi^E \rightarrow \pi$

(i) $\Delta Fuel \rightarrow \Delta ER$ (j) $\pi \rightarrow \Delta ER$ (k) $\Delta ER \rightarrow \Delta ER$ (l) $\pi^E \rightarrow \Delta ER$

(m) $\Delta Fuel \rightarrow \pi^E$ (n) $\pi \rightarrow \pi^E$ (o) $\Delta ER \rightarrow \pi^E$ (p) $\pi^E \rightarrow \pi^E$

Source: Authors' own calculations based on national sources and IMF commodity price data.
Note: Response to a one standard deviation shock of the relevant variable. The median value and 66% confidence intervals are reported.

Fig. A.8. Peru: Impulse-Response Functions, Baseline Model



(a) $\Delta Fuel \rightarrow \Delta Fuel$ (b) $\pi \rightarrow \Delta Fuel$ (c) $\Delta ER \rightarrow \Delta Fuel$ (d) $\pi^E \rightarrow \Delta Fuel$

(e) $\Delta Fuel \rightarrow \pi$ (f) $\pi \rightarrow \pi$ (g) $\Delta ER \rightarrow \pi$ (h) $\pi^E \rightarrow \pi$

(i) $\Delta Fuel \rightarrow \Delta ER$ (j) $\pi \rightarrow \Delta ER$ (k) $\Delta ER \rightarrow \Delta ER$ (l) $\pi^E \rightarrow \Delta ER$

(m) $\Delta Fuel \rightarrow \pi^E$ (n) $\pi \rightarrow \pi^E$ (o) $\Delta ER \rightarrow \pi^E$ (p) $\pi^E \rightarrow \pi^E$

Source: Authors' own calculations based on national sources and IMF commodity price data.
Note: Response to a one standard deviation shock of the relevant variable. The median value and 66% confidence intervals are reported.

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