Exchange Rate Pass-Through, Price Dollarization, and Monetary Policy: The Costa Rican Experience

Fabio Gómez-Rodríguez*
Catalina Sandoval†

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Abstract

We examine whether exchange rate pass-through (ERPT) estimates accurately reflect the exchange rate's role in domestic inflation. In small open economies such as Costa Rica, only a small share of exchange rate fluctuations is attributable to exogenous shocks. Most structural models used to estimate the ERPT effect focus exclusively on these shocks, omitting systematic exchange rate movements that may have substantial effects on prices. We estimate a structural VAR model that identifies inflation's response to all exchange rate variations. A 1 percentage point increase in the annual exchange rate change raises inflation by 0.04 percentage points when driven by an exchange rate shock, but by 0.25 percentage points when the change is systematic. The large gap between these estimates reconciles the puzzle of low ERPT coefficients with the widespread perception that exchange rate movements strongly influence inflation. It also clarifies why the exchange rate, despite its comovement with inflation, is an ineffective instrument for inflation control.

Keywords: Exchange Rate Pass-Through, Monetary Policy, SVAR
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*Lehigh University, Economic Research Department, Central Bank of Costa Rica (gomezrj@bccr.fi.cr)

†Economic Research Department, Central Bank of Costa Rica (sandovalac@bccr.fi.cr)

1 Introduction

Exchange rate pass-through (ERPT) measures how exchange rate fluctuations affect domestic inflation. In Costa Rica, standard estimates suggest that a 1% depreciation of the Costa Rican colón against the US dollar raises annual CPI inflation by only 0.04 percentage points. For a small open economy pursuing low and stable inflation, such a low ERPT is desirable—but it seems insufficient to capture the prominent role the exchange rate appears to play in the country's price-setting process.

Using a monthly dataset from July 2006 to May 2025, we find that exchange rate movements are closely interconnected with consumer prices at the micro level. In the Costa Rican CPI basket, 135 of 289 goods and services increase their annual price change by at least 0.32 percentage points on average following a 1% depreciation, and the number of positively correlated items rises to 162 a few months following the exchange rate variation. We refer to this phenomenon as *price dollarization*: the tendency of domestic prices to track the US dollar exchange rate, even in a low-dollarized economy (Drenik and Perez, 2020). This raises a puzzle: why do aggregate ERPT estimates remain so low?

A key reason lies in the conventional ERPT estimation strategy. Structural models typically identify the causal effect of the exchange rate on inflation using only *exogenous* exchange rate shocks. If the nominal exchange rate behaves like a random walk, this approach captures most of its variability. But when, as in Costa Rica, exogenous shocks explain only a fraction of exchange rate movements, such estimates provide an incomplete picture of the inflation–exchange rate link.

Shambaugh (2008a) and related work (Forbes et al., 2018; Ha et al., 2020; García-Cicco and García-Schmidt, 2020) propose *conditional* ERPT measures—responses of inflation to exchange rate changes triggered by specific shocks, such as monetary policy or aggregate demand disturbances. While informative, these measures cannot isolate the portion of inflation's response attributable solely to the exchange rate.

Our approach departs from this literature by adapting methods from the monetary policy identification literature (Leeper, 1997; Baumeister and Hamilton, 2018; Arias et al., 2019). We estimate a structural VAR that explicitly models the inflation "rule" and identifies the weight of exchange rate variations—both systematic and shock-driven—in the process that determines inflation. This *systematic ERPT* measure reflects the contribution of exchange rate movements to inflation under the prevailing policy and economic environment.

We find a short-term unconditional pass-through semi-elasticity of about 4%, rising to 9% at the five months horizon. Our measure of systematic ERPT suggests that a 1% year-on-year depreciation produces a contemporaneous inflationary impact of 0.25 percentage points—over six times larger than the unconditional estimate.

This large gap reconciles the low ERPT coefficients found in conventional estimates with the widespread perception that exchange rate movements strongly influence inflation. It also explains why, despite comoving with inflation, the exchange rate is an ineffective instrument for controlling it.

The remainder of the paper is structured as follows. Section 2 describes the structural model. Section 3 outlines the estimation strategy. Section 4 presents the results across different ERPT measures, and Section 5 concludes with policy implications.

2 A Structural Model for Exchange Rate Pass-Through

The structural model employed in this paper consists of a system of equations explicitly describing the interactions among key economic variables. Unlike traditional reduced-form approaches, our structural framework allows for a clear interpretation of causal relationships and provides a robust foundation for policy analysis. Specifically, the model characterizes how domestic inflation dynamically responds to changes in the exchange rate, domestic monetary policy rates, and external economic conditions, as represented by U.S. inflation and interest rates. Although the model abstracts from some potentially influential factors, it offers an economically meaningful representation suitable for exploring exchange rate pass-through (ERPT) dynamics.

The structural formulation leverages contemporaneous and lagged relationships between variables to facilitate precise identification of economic shocks. This approach offers flexibility in imposing theory-driven identification restrictions, thereby significantly enhancing the clarity and interpretability of the estimated structural parameters.

The core variables of our analysis include Costa Rican CPI inflation (π_t), the monetary policy rate of Costa Rica (i_t), the USD-CRC nominal exchange rate (x_t), as well as U.S. CPI inflation (π_t^{USA}) and the federal funds rate (i_t^{USA}). We employ the notation $f_z(\mathfrak{F}_{t-1})$ to denote the dynamic dependence of any given variable z_t on the entire set of information available up to time $t-1$, represented as $\mathfrak{F}_{t-1}$.

2.1 Model Equations

Below, we detail the structural equations underpinning the model, each guided by economic theory and tailored specifically to reflect the context of the Costa Rican economy.

Inflation Equation. The structural equation governing inflation (π_t) explicitly incorporates contemporaneous interactions with the U.S. monetary stance and inflation ($i_t^{\text{USA}}, \pi_t^{\text{USA}}$), the domestic exchange rate (x_t), and Costa Rica's monetary policy rate (i_t). The inflation equation takes the following form:

$$\pi_t = c^{\pi} + \boldsymbol{\eta}^{\boldsymbol{i}} i_t^{\text{USA}} + \boldsymbol{\eta}^{\boldsymbol{\pi}} \pi_t^{\text{USA}} + \boldsymbol{\beta} x_t + \boldsymbol{\tau} i_t + f_{\pi}(\mathfrak{F}_{t-1}) + \sigma^{\pi} \epsilon_t^{\pi}, \tag{1}$$

Economic theory motivates the following sign restrictions on parameters in equation (1):

- $\boldsymbol{\eta}^{\boldsymbol{i}}$: No restriction imposed, as the net effect of U.S. interest rates on Costa Rican inflation is theoretically ambiguous.
- $\boldsymbol{\eta}^{\boldsymbol{\pi}}$: Positive, as higher U.S. inflation typically transmits inflationary pressures through imported goods.
- $\boldsymbol{\beta}$: Positive, reflecting the conventional view that currency depreciations systematically elevate domestic prices.

- $\boldsymbol{\tau}$: Negative, consistent with standard monetary policy transmission mechanisms where higher interest rates reduce inflation through diminished aggregate demand.

Nominal Exchange Rate Equation. The nominal exchange rate equation captures how domestic and foreign economic conditions shape exchange rate dynamics:

$$x_t = c^x + \boldsymbol{\kappa^i} i_t^{\text{USA}} + \boldsymbol{\kappa^\pi} \pi_t^{\text{USA}} + \boldsymbol{\phi} i_t + \boldsymbol{\alpha} \pi_t + f_x(\mathfrak{F}_{t-1}) + \sigma^x \epsilon_t^x. \tag{2}$$

Guided by economic intuition, we impose the following sign restrictions:

- $\boldsymbol{\kappa^i}$: Positive, as higher U.S. interest rates strengthen the dollar relative to the colón.
- $\boldsymbol{\kappa^\pi}$: Negative, given that rising U.S. inflation typically depreciates the dollar.
- $\boldsymbol{\phi}$: Negative, since higher domestic interest rates attract capital flows, appreciating the colón.
- $\boldsymbol{\alpha}$: Positive, reflecting depreciation pressures from elevated domestic inflation.

The structural interpretation of shocks (ϵ_t^x) allows us to clearly differentiate between systematic pass-through (captured by β) and traditional shock-based pass-through.

The subsequent equations describing monetary policy and the U.S. sector are similarly structured and will be presented in detail in the following subsections.

Monetary Policy in Costa Rica. The monetary policy equation captures the systematic behavior of Costa Rica's Central Bank in setting the monetary policy rate (i_t). This formulation reflects the central bank's primary mandate to maintain low and stable inflation, explicitly incorporating its responses to domestic inflation, exchange rate movements, and external variables such as U.S. inflation and interest rates. While the equation represents an approximation rather than a precise policy rule, it aligns well with theoretical expectations and practical considerations of monetary policy decision-making:

$$i_t = c^i + \boldsymbol{\xi^i} i_t^{\text{USA}} + \boldsymbol{\xi^\pi} \pi^{\text{USA}} t + \boldsymbol{\delta} x_t + \boldsymbol{\gamma} \pi_t + f_i(\mathfrak{F} t - 1) + \sigma^i \epsilon_t^i. \tag{3}$$

Each parameter in equation (3) is subject to positive sign restrictions. Specifically, U.S. inflation and the nominal exchange rate affect the domestic policy rate indirectly via their influence on inflation expectations. The positive relationship with the U.S. interest rate also reflects coordinated responses to global financial conditions and the aim to ensure stability in Costa Rican financial markets.

U.S. Sector Model. The model also incorporates U.S. monetary conditions, assuming exogeneity relative to Costa Rican variables. Specifically, we define the U.S. monetary sector through the following equations:

$$i_t^{\text{USA}} = c^{i^{\text{USA}}} + \boldsymbol{\theta^\pi} \pi^{\text{USA}} t + f i^{\text{USA}}(\mathfrak{F}_{t-1}) + \sigma^{i^{\text{USA}}} \epsilon_t^{i^{\text{USA}}}, \tag{4}$$

$$\pi_t^{\text{USA}} = c^{\pi^{\text{USA}}} + \boldsymbol{\theta^i} i^{\text{USA}} t + f \pi^{\text{USA}}(\mathfrak{F}_{t-1}) + \sigma^{\pi^{\text{USA}}} \epsilon_t^{\pi^{\text{USA}}}. \tag{5}$$

We impose standard economic theory-based sign restrictions ($\theta^{\pi} > 0$ and $\theta^{i} < 0$), and assume no contemporaneous or lagged responses of U.S. variables to Costa Rican economic developments, reflecting Costa Rica's role as a small open economy and price-taker internationally.

Table 1: Summary of Identification Restrictions

Parameter	Effect of ...	Sign
η^{i}	U.S. interest rate on Costa Rican inflation.	*
η^{π}	U.S. inflation on Costa Rican inflation.	+
β	Exchange rate on Costa Rican inflation.	+
τ	Costa Rican interest rate on inflation.	-
κ^{i}	U.S. interest rate on exchange rate.	+
κ^{π}	U.S. inflation on exchange rate.	-
ϕ	Costa Rican interest rate on exchange rate.	-
α	Costa Rican inflation on exchange rate.	+
ξ^{i}	U.S. interest rate on Costa Rican interest rate.	+
ξ^{π}	U.S. inflation on Costa Rican interest rate.	+
δ	Exchange rate on Costa Rican interest rate.	+
γ	Costa Rican inflation on interest rate.	+
θ^{π}	U.S. inflation on U.S. interest rate.	+
θ^{i}	U.S. interest rate on U.S. inflation.	-

Note: "*" indicates a parameter with no sign restriction, "+" indicates a positive restriction, and "-" indicates a negative restriction.

2.2 Structural Vector Autoregressive Model

By integrating equations (1)-(5), a system is formed that can be expressed as a Structural Vector Autoregressive (SVAR) model. This system is designed so that the results do not depend on the ordering of the variables. However, to compare this model with others in which the order of the variables is relevant, the equations have been arranged so that the potentially "most exogenous" variable appears first, while the "most endogenous" one is placed last in the definition of the vector y_t. In matrix form, this model is written as follows[1]:

$$\begin{bmatrix} 1 & -\theta^{\pi} & 0 & 0 & 0 \\ -\theta^{i} & 1 & 0 & 0 & 0 \\ -\kappa^{i} & -\kappa^{\pi} & 1 & -\phi & -\alpha \\ -\xi^{i} & -\xi^{\pi} & -\delta & 1 & -\gamma \\ -\eta^{i} & -\eta^{\pi} & -\beta & -\tau & 1 \end{bmatrix} \begin{pmatrix} i_t^{\text{USA}} \\ \pi_t^{\text{USA}} \\ x_t \\ i_t \\ \pi_t \end{pmatrix} = \begin{pmatrix} c^{i^{\text{USA}}} \\ c^{\pi^{\text{USA}}} \\ c^{x} \\ c^{i} \\ c^{\pi} \end{pmatrix} + \begin{pmatrix} f_{i^{\text{USA}}}(\mathfrak{F}_{t-1}) \\ f_{\pi^{\text{USA}}}(\mathfrak{F}_{t-1}) \\ f_x(\mathfrak{F}_{t-1}) \\ f_i(\mathfrak{F}_{t-1}) \\ f_{\pi}(\mathfrak{F}_{t-1}) \end{pmatrix} + \begin{pmatrix} \sigma^{i^{\text{USA}}} \epsilon_t^{i^{\text{USA}}} \\ \sigma^{\pi^{\text{USA}}} \epsilon_t^{\pi^{\text{USA}}} \\ \sigma^{x} \epsilon_t^{x} \\ \sigma^{i} \epsilon_t^{i} \\ \sigma^{\pi} \epsilon_t^{\pi} \end{pmatrix}.$$

The model identifies five structural shocks[2]: two originating from the U.S. economy, related to monetary policy ($\epsilon_t^{i^{\text{USA}}}$) and prices ($\epsilon_t^{\pi^{\text{USA}}}$); one associated with the exchange rate (ϵ_t^{x}); and two local shocks, corresponding to monetary policy (ϵ_t^{i}) and prices (ϵ_t^{π}).

[1] The detailed process for formulating the model in matrix form is found in Appendix D.

[2] By introducing the parameters ($\sigma^{i^{\text{USA}}}, \sigma^{\pi^{\text{USA}}}, \sigma^{x}, \sigma^{i}, \sigma^{\pi}$), these shocks are normalized.

The model variables define the vector y_t as:

$$y_t = \begin{pmatrix} i_t^{\text{USA}} & \pi_t^{\text{USA}} & x_t & i_t & \pi_t \end{pmatrix}'.$$

To represent $f_y(\mathfrak{F}_{t-1})$, we simplify the presentation by considering the case in which y_t follows a first-order vector autoregressive process ($p = 1$)[3]. Under this assumption, the model can be compactly expressed as:

$$Ay_t = c + \tilde{B}y_{t-1} + D^{1/2}\boldsymbol{\epsilon}_t, \tag{6}$$

where D is the diagonal matrix of structural shock variances. By construction, the square root of this matrix, $D^{1/2}$, corresponds to a diagonal matrix whose elements are the standard deviations of the structural shocks.

The reduced form[4] of this model is obtained by multiplying both sides by the inverse of A:

$$\begin{aligned} y_t &= A^{-1}c + A^{-1}\tilde{B}y_{t-1} + A^{-1}D^{1/2}\boldsymbol{\epsilon} \\ y_t &= \tilde{c} + \Phi y_{t-1} + H\boldsymbol{\epsilon} \\ y_t &= \tilde{c} + \Phi y_{t-1} + u_t, \end{aligned} \tag{7}$$

where $\tilde{c} = A^{-1}c$, $\Phi = A^{-1}\tilde{B}$, and $H = A^{-1}D^{1/2}$.

Difference between specifications. The model described by equation 6, through the matrix A, parameterizes the contemporaneous relationships between the endogenous variables of the system. For example, this specification allows analyzing how inflation (π_t) responds to a variation in the exchange rate (x_t) through the coefficient β. This structural approach is useful for identifying causal relationships and analyzing the impact of specific shocks, which requires explicit assumptions about the contemporaneous restrictions among the variables.

On the other hand, equation 7 is expressed in *reduced form*. In this case, the terms u_t represent one-step-ahead forcast errors, which are linear combinations of the structural shocks. While the reduced-form model focuses on the predictive capacity of the variables, it does not directly provide information about contemporaneous causality. This contrast with structural models reflects their emphasis on describing the dynamic behavior of variables rather than explaining the underlying interactions of the system.

A *structural* model characterizes either the matrix A or the matrix H. The most common practice is to specify H, often as a triangular matrix (Cholesky). The matrix A describes the contemporaneous relationships between the endogenous variables of the system, while the matrix H characterizes how each variable responds to each structural shock.

In practical terms, the matrix A measures, for example, the contemporaneous response of inflation to a variation in the exchange rate (x_t). In contrast, the matrix H measures the response of inflation to an unexpected movement in the exchange rate, that is, a shock (ϵ^x) that cannot be predicted from other variables in the model. In this sense, H captures how variables react to structural shocks.

[3] In practice, we use $p = 12$.

[4] The reduced form corresponds to the formulation of y_t as a vector autoregressive (VAR) model.

2.3 Shock Identification Schemes

In the SVAR model literature, the identification problem arises because a VAR model, estimated in its reduced form, only allows observing the covariance matrix of the residuals, $\Omega = HH'$, as indicated in equation 7. A VAR model becomes structural when the components of H are identified, either explicitly or implicitly through the matrix A. Without identification assumptions, it is not possible to determine the specific elements of either of these matrices.

Our model highlights the importance of adopting a structural approach. For example, in the face of an unexpected increase in U.S. inflation (an international price shock), the model predicts a depreciation of the dollar against the colón, that is, a decrease in (x_t). At the same time, the increase in import prices generates a rise in Costa Rican inflation (π_t). Without a structural model capturing these relationships, only a drop in the exchange rate and an increase in inflation would be observed, which could lead to a misinterpretation of the pass-through effect as negative. The inability to identify the different shocks influencing these variables would lead non-structural models to estimate a downward-biased pass-through effect.

The model we present imposes few restrictions, which are justified by economic theory. These restrictions are reflected in the matrix A, where the zeros in the first two rows represent exclusion restrictions.

$$A = \begin{bmatrix} 1 & -\theta^{\pi} & 0 & 0 & 0 \\ -\theta^{i} & 1 & 0 & 0 & 0 \\ -\kappa^{i} & -\kappa^{\pi} & 1 & -\phi & -\alpha \\ -\xi^{i} & -\xi^{\pi} & -\delta & 1 & -\gamma \\ -\eta^{i} & -\eta^{\pi} & -\beta & -\tau & 1 \end{bmatrix}$$

Next, we will discuss the implications that using the most common identification strategy in the literature on the pass-through effect in Costa Rica—known as recursive, triangular, or Cholesky identification—would have on our model.

Identification of *Cholesky*. The most commonly used identification assumption, due to its simplicity, is the triangular or *Cholesky* assumption, which assumes that H has a triangular structure. Analyzing[5] the matrix H, obtained by inverting matrix A and multiplying it by the square root of matrix D, it is observed that for it to be triangular, the following conditions must hold:

$$\begin{aligned} \phi + \alpha\tau &= 0, \\ \alpha + \gamma\phi &= 0, \\ \gamma + \alpha\delta &= 0, \end{aligned}$$

where the parameters are the same as those forming matrix A. Since these equations generate a system with three restrictions and five parameters, the solutions are expressed in terms of δ and γ.

The first solution arises in the most general case, when $\delta \neq 0$ and $\gamma \neq 0$:

$$(\alpha, \tau, \phi) = \left(\frac{-\gamma}{\delta}, \frac{1}{\gamma}, \frac{1}{\delta} \right).$$

[5] Appendix B details the explicit form of H in terms of the parameters of matrices A and D.

Since δ and γ must be positive, due to identifying restrictions, this solution implies that the response of the nominal exchange rate to an increase in inflation (α) is negative, meaning that inflation would appreciate the colón. Additionally, τ would be positive, suggesting that inflation increases with the interest rate and that the colón depreciates when it rises ($\phi > 0$). However, these restrictions are difficult to justify from economic theory.

If $\gamma = 0$ but $\delta \neq 0$, we obtain:

$$(\alpha, \gamma, \phi) = (0, 0, 0),$$

with τ and δ free. This implies that prices in Costa Rica do not affect the nominal exchange rate ($\alpha = 0$), that monetary policy does not respond to inflation ($\gamma = 0$), and that the interest rate does not influence the exchange rate ($\phi = 0$). Again, these restrictions are not realistic in a macroeconomic model.

If $\delta = 0$, the solution is:

$$(\alpha, \gamma, \delta, \phi) = (0, 0, 0, 0),$$

with τ free. This would have implications similar to those mentioned in the previous case, making it equally implausible.

Additionally, for H to be triangular, it is required that $\theta^{\pi} = 0$, implying that U.S. monetary policy does not respond to inflation. This assumption lacks economic support.

In conclusion, the triangular (Cholesky) identification imposes, sometimes subtly, a series of restrictions that are not defensible from economic theory. Although these conclusions depend on the variables and the specific order used in our model, we consider that these arguments justify a critical review of the conclusions and estimates derived from models using this identification strategy in other contexts, specifically in previous estimates of the pass-through effect in Costa Rica.

2.4 The Different Types of Pass-Through Effects

The model proposed in this study has been designed to explicitly examine the conditional and unconditional pass-through effects, which have already been discussed in the literature (García-Cicco and García-Schmidt, 2020; Shambaugh, 2008b; Ha et al., 2020), as well as the systematic pass-through effect, introduced in this research.

The Systematic Pass-Through Effect. It is the combination of price dollarization and a certain degree of exchange rate predictability that underscores the significance of the systematic exchange rate pass-through effect. In the following section, we explore exchange rate predictability in small or shallow markets, specifically focusing on the U.S. dollar market in Costa Rica.

Academic evidence suggests that in larger and more liquid foreign exchange markets, such as those for the U.S. dollar or the euro, exchange rates typically exhibit behavior closely resembling a "random walk" (Meese and Rogoff, 1983; Evans and Lyons, 2002). In contrast, smaller economies with less developed foreign exchange markets often have concentrated market activity among a few significant players, providing predictive opportunities due to reduced competition and the disproportionate impact of their trading operations (Lyons, 2001). Additionally, studies by the Bank for International Settlements (BIS) (2022) highlight significant differences in trading volume and liquidity across currencies, directly influencing how quickly information is assimilated into market prices and thus affecting exchange rate predictability.

Moreover, the relative predictability of the U.S. dollar exchange rate, coupled with a certain degree of local price dollarization, can systematically shape domestic price formation in small open economies. This dynamic implies that fluctuations in exchange rates rapidly affect domestic prices, particularly when inputs or consumer goods are priced in dollars (Goldberg and Knetter, 1997). Consequently, even minor exchange rate movements can significantly impact local inflation, as economic agents frequently adjust their price and wage expectations based on dollar behavior.

The *systematic pass-through effect*, as defined in this study, encapsulates this channel through which exchange rates influence domestic prices. It is derived from estimating the inflation determination equation (see equation 1). While economic reasoning suggests that this parameter is unlikely to be constant throughout the economy—given its potential variability depending on the direction and magnitude of exchange rate shifts, product or service categories, or temporal factors—we currently represent it uniformly through the parameter β.[6]

The Unconditional Pass-Through Effect. The expression for the unconditional exchange rate pass-through (PT)—that is, the impact response of inflation (π_t) to an exchange rate shock (ϵ_t^x)—is particularly insightful, as it explicitly quantifies the pass-through multiplier from exchange rate shocks to domestic prices. Formally, based on the H matrix, it is given by:

$$\mathrm{PT}_{\text{uncond.}} = \frac{\beta + \delta\tau}{1 - \gamma\tau},$$

where β captures the direct impact of exchange rate changes on inflation and is assumed to be positive. The parameter τ measures inflation's responsiveness to monetary policy actions, and is restricted to negative values. Additionally, δ represents the responsiveness of monetary policy to movements in the exchange rate, and γ denotes how aggressively monetary policy reacts to inflationary pressures, both assumed positive. The critical insight from this expression lies in its explanation of how a relatively high direct exchange rate impact on inflation (β) can coexist with a low observed pass-through. This apparent contradiction arises precisely because of effective monetary policy interventions (δ and γ) that moderate inflationary effects through strong counteracting responses to both exchange rate fluctuations and inflation itself. Consequently, the efficacy of monetary policy in stabilizing prices becomes the key factor mitigating the observed systematic exchange rate pass-through.

The Conditional Pass-Through Effect. The nominal exchange rate can vary for various reasons, which is reflected in our model through equation 2. This equation shows that the exchange rate responds to variations in interest rates, prices, and exchange rate-specific shocks. According to Shambaugh (2008b), the pass-through effect—that is, the response of prices to exchange rate variations—may differ depending on the origin of the shock causing these fluctuations.

[6] Future research could explore models relaxing this assumption.

In our model, there are four shocks in addition to the exchange rate-specific one, one for each variable in the system. Therefore, we can calculate the conditional pass-through effect for each of these four shocks. This is measured as follows:

$$\mathrm{PT}_w(h) = \frac{\sum_{i=0}^{h} \mathrm{resp}(\pi_{t+i}, \epsilon_t^w)}{\sum_{i=0}^{h} \mathrm{resp}(z_{t+i}, \epsilon_t^w)}, \tag{8}$$

where $\mathrm{resp}(z_{t+h}, \epsilon_t^w)$ represents the response of variable z in period $t+h$ to a shock ϵ_t^w. This response is calculated as the difference between the trajectory of z conditioned on a shock[7] w and its trajectory without that shock.

In expression 8, the factor causing the inflation variation is w, not necessarily the exchange rate. For this reason, this measure has the limitation of not exclusively capturing the effects of the nominal exchange rate on prices. Instead, the effects of the exchange rate are combined with those of the corresponding shock (w).

The unconditional and conditional pass-through effects are comparable since both are expressed in same units. However, to compare the systematic pass-through effect with the first two, it is necessary to adjust its value using averages or the final observations of the sample corresponding to the nominal exchange rate and the price index.

Proposition 1 (Why shock-based ERPT understates total ERPT when ER shocks explain little FX variance)**.** *Let the inflation determination equation include the nominal exchange rate as*

$$\pi_t \;=\; \beta x_t \;+\; g(F_{t-1}) \;+\; u_t, \tag{9}$$

where $g(F_{t-1})$ *is any (possibly high-dimensional) function of information dated* $t-1$*, and* u_t *is an error term orthogonal to the structural shocks defined below. Assume the nominal exchange rate admits the (one-period) structural representation*

$$x_t \;=\; a_x \varepsilon_t^x \;+\; \sum_{j\neq x} a_j \varepsilon_t^j, \tag{10}$$

where the shocks $\{\varepsilon_t^j\}_j$ *are mutually orthogonal with* $\mathrm{Var}(\varepsilon_t^j) = \sigma_j^2$ *and* $\mathrm{Cov}(\varepsilon_t^j, \varepsilon_t^\ell) = 0$ *for* $j \neq \ell$*.*

Define the shock-based pass-through *(as in conventional SVAR ERPT, identified from the exchange-rate shock) as*

$$PT^{shock} \;\equiv\; \frac{\mathrm{Cov}(\pi_t, \varepsilon_t^x)}{\mathrm{Var}(\varepsilon_t^x)},$$

and define the variance share *of the exchange-rate shock in the nominal exchange rate as*

$$\omega_x \;\equiv\; \frac{\mathrm{Var}(a_x \varepsilon_t^x)}{\mathrm{Var}(x_t)} \;=\; \frac{a_x^2 \sigma_x^2}{\mathrm{Var}(x_t)} \in [0,1].$$

Then:

[7] This could be any of those included in the model: $\epsilon_t^{i^{\mathrm{USA}}}$, $\epsilon_t^{\pi^{\mathrm{USA}}}$, ϵ_t^{i}, or ϵ_t^{π}.

(i) $PT^{shock} = \beta a_x$.

(ii) If $\mathrm{Var}(x_t)$ *is fixed,* $|PT^{shock}|$ *is proportional to* $\sqrt{\omega_x}$*:*

$$|PT^{shock}| \;=\; |\beta|\sqrt{\omega_x}\,\sqrt{\frac{\mathrm{Var}(x_t)}{\sigma_x^2}}.$$

In particular, holding β*,* $\mathrm{Var}(x_t)$*, and* σ_x^2 *fixed, a small variance share* ω_x *mechanically implies a small shock-based ERPT estimate.*

Proof. Using (9) and (10),

$$\mathrm{Cov}(\pi_t, \varepsilon_t^x) = \mathrm{Cov}(\beta x_t + g(F_{t-1}) + u_t,\ \varepsilon_t^x) = \beta\,\mathrm{Cov}(x_t, \varepsilon_t^x),$$

where the last equality uses $\mathrm{Cov}(g(F_{t-1}), \varepsilon_t^x) = 0$ and $\mathrm{Cov}(u_t, \varepsilon_t^x) = 0$ by assumption. From (10) and shock orthogonality,

$$\mathrm{Cov}(x_t, \varepsilon_t^x) = \mathrm{Cov}\left(a_x\varepsilon_t^x + \sum_{j\neq x} a_j\varepsilon_t^j,\ \varepsilon_t^x\right) = a_x\,\mathrm{Var}(\varepsilon_t^x) = a_x\sigma_x^2.$$

Therefore,

$$PT^{\text{shock}} = \frac{\mathrm{Cov}(\pi_t, \varepsilon_t^x)}{\mathrm{Var}(\varepsilon_t^x)} = \frac{\beta a_x\sigma_x^2}{\sigma_x^2} = \beta a_x,$$

which proves (i). For (ii), note that $\omega_x = a_x^2\sigma_x^2/\mathrm{Var}(x_t)$ implies $a_x = \sqrt{\omega_x}\sqrt{\mathrm{Var}(x_t)/\sigma_x^2}$ (taking absolute values if needed), hence $|PT^{\text{shock}}| = |\beta||a_x| = |\beta|\sqrt{\omega_x}\sqrt{\mathrm{Var}(x_t)/\sigma_x^2}$. □

3 Model Estimation

Estimating structural models, such as the one proposed here, requires sophisticated techniques to unravel causal relationships in economic data. A commonly used framework is Structural Vector Autoregressive Models (SVAR), which allow researchers to estimate the dynamic effects of shocks on macroeconomic variables while imposing minimal theoretical restrictions. This approach involves identifying structural shocks by applying constraints, such as sign and zero restrictions on impulse responses or structural relationships among endogenous variables, to ensure that the estimated relationships are consistent with economic theory.

Baumeister and Hamilton (2015) highlight the integration of Bayesian inference, which incorporates prior beliefs and enables a systematic exploration of uncertainty in model parameters. This methodology provides a flexible and robust framework for assessing the effects of monetary policy shocks and other economic phenomena, making it a fundamental pillar of contemporary econometric modeling. This section describes the technical aspects of the model specification and estimation outlined in the previous section. It is intended for readers interested in reviewing or replicating this methodology. Those primarily interested in the results are encouraged to proceed to the next section.

3.1 Model Specification

The main specification of the model to be estimated is defined as:

$$Ay_t = c + \tilde{B}y_{t-1} + D^{1/2}\boldsymbol{\epsilon}, \tag{6}$$

$$Ay_t = B\boldsymbol{x_{t-1}} + D^{1/2}\boldsymbol{\epsilon}, \tag{11}$$

where $B = \begin{bmatrix}\tilde{B} & c\end{bmatrix}$ and $\boldsymbol{x_{t-1}} = \begin{bmatrix}y_{t-1} & 1\end{bmatrix}$. Here, we use a slight abuse of notation, as x_t, without emphasis, denotes the annual rate of change of the nominal exchange rate. The matrices A and D are of dimensions $n \times n$, where n represents the number of variables in y_t. It is important to note that D is a diagonal matrix. Meanwhile, B has dimensions $n \times k$, with $k = mn + 1$, where m corresponds to the number of lags considered.

The estimation of this model is based on the Bayesian methodology developed by Baumeister and Hamilton (2015) and Baumeister and Hamilton (2018). For this approach we postulate a prior distribution for each element in A known as the *prior* distribution. Conditional on A, the *prior* distribution of the elements of D is specified, and, in turn, conditional on A and D, the *prior* distribution of B is described.

In *Proposition 1* of Baumeister and Hamilton (2015), it is detailed how, through integration, the marginal function of the *posterior* distribution[8] can be obtained in terms of the free elements of A. Using a *Metropolis-Hastings* algorithm[9], samples of the model's *posterior* distribution can be generated. This distribution reflects a balance between how well the parameters conform to the *prior* distribution and their ability to explain the observed data.

An important feature of the model is the ability to impose additional identification restrictions on the components of matrix B. This allows consideration of only parameters in which U.S. variables do not systematically respond to the lags of fluctuations in Costa Rican variables, such as the exchange rate, interest rate, and inflation. This restriction is reasonable for a small economy like Costa Rica.

In Baumeister and Hamilton (2018), the authors extend the model to allow for restrictions on matrix H. This makes it possible, for example, to impose that inflation in Costa Rica responds positively to exchange rate variations ($\beta > 0$) and to exchange rate shocks (ϵ_t^x). The latter restriction ensures a positive unconditional pass-through effect.

The formulation of these distributions and restrictions closely follows the approach presented by Baumeister and Hamilton (2015). Readers are encouraged to consult their work directly for more detailed information on the specifications and underlying theoretical foundations.

3.2 *A Priori* Distributions

Distribution of Matrix A. For the parameters that make up matrix A, we propose a distribution from the t family with three degrees of freedom, truncated pos-

[8]The *posterior* distribution incorporates information from observed data to update prior beliefs or knowledge about the parameters of a model. This concept is based on Bayes' theorem, which combines prior information with the likelihood of the data to provide a more informed parameter estimate.

[9]A description of the algorithm is included in Appendix E.

itively or negatively as deemed appropriate based on the identification restrictions (see Table 1).

To refer to the set of parameters in matrix A, we define the vector $\boldsymbol{\alpha}$ as follows, slightly abusing notation:

$$\boldsymbol{\alpha} = (\theta^{\pi} \quad \theta^{i} \quad \kappa^{i} \quad \kappa^{\pi} \quad \alpha \quad \phi \quad \xi^{i} \quad \xi^{\pi} \quad \delta \quad \gamma \quad \eta^{i} \quad \eta^{\pi} \quad \beta \quad \tau)'.$$

Table 2 presents the *a priori* distributions of the coefficients in matrix A related to U.S. interest rate and inflation variables. These parameters correspond to the first two columns of matrix A.

Table 2: *A Priori* Distributions of Elasticities to U.S. Variables

Parameter	Distribution	Mean	Standard Deviation
θ^{π}	t^{+}_{100}	1.5	0.4
θ^{i}	t^{-}_{100}	-1	1
κ^{i}	t^{+}_{3}	0.5	0.4
κ^{π}	t^{-}_{3}	-0.5	0.4
ξ^{i}	t^{+}_{3}	0.5	0.1
ξ^{π}	t^{+}_{3}	0.5	0.1
η^{i}	t_{3}	0	0.1
η^{π}	t^{+}_{3}	0.5	0.1

Note: The subscript in the distribution represents the number of degrees of freedom, and the superscript indicates whether the distribution is truncated positively (+) or negatively (-).

For the parameters describing the Costa Rican economy, the following set of *a priori* distributions is considered:

- For parameter ϕ, which represents the response of the nominal exchange rate (NER) to an increase in the monetary policy rate (TPM), we propose a t distribution with three degrees of freedom, a mean of -0.4, and truncated negatively. This reflects the fact that TPM increases appreciate the Costa Rican colón.

- For parameter α, which represents the response of the NER to an increase in Costa Rican inflation, we propose a t distribution with three degrees of freedom, a mean of 0.4, and truncated positively, indicating that Costa Rican inflation depreciates the colón.

- For parameter δ, which reflects the response of the TPM to an increase in the NER, we propose a t distribution with three degrees of freedom, a mean of 0.5, and truncated positively. This reflects that the TPM would respond positively to a depreciation of the Costa Rican colón that increases inflation expectations.

- For parameter γ, which represents the response of the TPM to an increase in Costa Rican inflation, we propose a t distribution with three degrees of freedom, a mean of 1.5, and truncated positively. This indicates that an increase in inflation is expected to be met with an increase in the interest rate as part of monetary policy.

- For parameter β, which measures the systematic pass-through effect, we propose a t distribution with three degrees of freedom, a mean of .2, and truncated positively, reflecting that increases in the NER put upward pressure on Costa Rican inflation.
- For parameter τ, which represents the response of inflation to an increase in the TPM, we propose a t distribution with three degrees of freedom, a mean of -1, and truncated negatively, indicating that inflation decreases with interest rate hikes.

The value of the *a priori* density function of matrix A is given by:

$$p(A) = p(\theta^{\pi})p(\theta^{i})p(\kappa^{i})p(\kappa^{\pi})\cdots p(\tau).$$

Distribution of Matrix D. Following Baumeister and Hamilton (2015), we specify a prior distribution for the diagonal elements of matrix D. In particular, each inverse diagonal element d_{ii}^{-1} is assumed to follow an inverse gamma distribution:

$$p\left(d_{ii}^{-1} \mid A\right) = \begin{cases} \frac{\tau_i^{\kappa_i}}{\Gamma(\kappa_i)}(d_{ii}^{-1})^{\kappa_i - 1}\exp(-\tau_i d_{ii}^{-1}) & \text{if } d_{ii}^{-1} \geq 0, \\ 0 & \text{otherwise,} \end{cases}$$

where $\kappa_i = 2$ and $\tau_i = 2 \cdot a_i' S a_i$. Here, a_i' denotes the i-th row of the matrix A, and S is a scaling matrix. Although not strictly necessary, including S aids in faster convergence of the algorithm. The matrix S can be constructed in various ways, such as the variance matrix of the reduced-form residuals of the model, or—as in this case—the covariance matrix of residuals from AR(4) or AR(8) models estimated individually for each variable.

Distribution of Matrix B. We place normal *a priori* distributions on the lagged structural coefficients in matrix B. Assuming these coefficients are independent across equations, each row vector $\mathbf{b}_i$ follows a multivariate normal distribution: $\mathcal{N}(\mathbf{m}_i, d_{ii}\mathbf{M}_i)$. This leads to a convenient factorization:

$$p(B \mid D, A) = \prod_{i=1}^{n} p(\mathbf{b}_i \mid D, A),$$

$$p(\mathbf{b}_i \mid D, A) = \frac{1}{(2\pi)^{k/2}|d_{ii}\mathbf{M}_i|^{1/2}} \exp\left[-\frac{1}{2}(\mathbf{b}_i - \mathbf{m}_i)'(d_{ii}\mathbf{M}_i)^{-1}(\mathbf{b}_i - \mathbf{m}_i)\right].$$

Here, $\mathbf{b}_i'$ denotes the i-th row of matrix B, representing the lagged coefficients in the i-th structural equation. The vector $\mathbf{m}_i$ is the prior mean, and $d_{ii}\mathbf{M}_i$ is the prior covariance. While both $\mathbf{m}_i$ and $\mathbf{M}_i$ may depend on A, they are assumed to be independent of D.

The prior mean $\mathbf{m}_i$, as a function of A, is given by $\mathbf{m}_i(\boldsymbol{\alpha}) = \eta' \mathbf{a}_i$, where:

$$\eta = \begin{bmatrix} I_n & 0 & \cdots & 0 & 0 \end{bmatrix},$$

with I_n denoting the identity matrix and the zeros representing $n \times n$ blocks, one for each higher-order lag. Let $\sqrt{s_{ii}}$ be the estimated standard deviation from an eighth-order univariate autoregression for variable i. Define:

$$\mathbf{v}_1' = \left(\frac{1}{1^{2\lambda_1}}, \frac{1}{2^{2\lambda_1}}, \dots, \frac{1}{m^{2\lambda_1}}\right), \quad \mathbf{v}_2' = \left(s_{11}^{-1}, s_{22}^{-1}, \dots, s_{nn}^{-1}\right)',$$

$$\mathbf{v}_3 = \lambda_0^2 \begin{bmatrix} \mathbf{v}_1 \otimes \mathbf{v}_2 \\ \lambda_3^2 \end{bmatrix}.$$

We then define $\mathbf{M}_i$ as a diagonal matrix with elements $M_{i,rr} = v_{3r}$. Following Doan et al. (1984), we set the hyperparameters as follows: $\lambda_1 = 1$, which controls how fast the prior variances decline with lag length; $\lambda_3 = 100$, making the prior on the intercept nearly non-informative; and $\lambda_0 = 0.2$, reflecting the overall tightness of the prior.

3.3 Sampling the *A Posteriori* Distribution

Model estimation requires generating samples from the *a posteriori* distribution $p(\mathbf{A}, \mathbf{D}, \mathbf{B} \mid \mathbf{Y}_T)$. This process utilizes a sampling scheme based on the Metropolis-Hastings technique with a random walk step.

The procedure starts with an initial value for the parameter vector of matrix A:

$$\boldsymbol{\alpha}^{(1)} = \hat{\boldsymbol{\alpha}}.$$

From this point, a new candidate is proposed using:

$$\tilde{\boldsymbol{\alpha}}^{(\ell+1)} = \boldsymbol{\alpha}^{(\ell)} + \xi(\hat{\mathbf{P}}_\Lambda^{-1})'\mathbf{v}_{\ell+1},$$

where $\mathbf{v}_{\ell+1}$ is a $n_p \times 1$ vector whose entries are independent standard normal variables. The parameter ξ is an adjustment factor (e.g., $\xi = 1.3$) designed to achieve an acceptance rate close to 30%, a concept that will be discussed later. The matrix $\hat{\mathbf{P}}_\Lambda$ can be defined in various ways. In this case, we use the Cholesky factor of the inverse Hessian evaluated at the maximum of function $q(\boldsymbol{\alpha})$, described in equation 12. An alternative is to use the identity matrix for $\hat{\mathbf{P}}_\Lambda$, simplifying implementation but leading to slower convergence.

$$\begin{aligned} q(\boldsymbol{\alpha}) = &\log p(\boldsymbol{\alpha}) + \frac{T}{2}\log\left\{\det\left[\mathbf{A}(\boldsymbol{\alpha})\hat{\boldsymbol{\Omega}}_T\mathbf{A}(\boldsymbol{\alpha})'\right]\right\} \\ &- \sum_{i=1}^{2}\left(\kappa_i + \frac{T}{2}\right)\log\left\{\frac{2\tau_i(\boldsymbol{\alpha})}{T} + \frac{\zeta_i^*(\boldsymbol{\alpha})}{T}\right\} \\ &+ \sum_{i=1}^{2}\kappa_i \log \tau_i(\boldsymbol{\alpha}), \end{aligned} \tag{12}$$

The definition of $\zeta_i^*(\boldsymbol{\alpha})$ follows from *Proposition 1* in Baumeister and Hamilton (2015), which is detailed in the appendix.

For each candidate $\tilde{\boldsymbol{\alpha}}^{(\ell+1)}$, we evaluate $q(\boldsymbol{\alpha})$ at the new point. If $q(\tilde{\boldsymbol{\alpha}}^{(\ell+1)}) < q(\boldsymbol{\alpha}^{(\ell)})$, the candidate is rejected with probability:

$$1 - \exp[q(\tilde{\boldsymbol{\alpha}}^{(\ell+1)}) - q(\boldsymbol{\alpha}^{(\ell)})].$$

Otherwise, the candidate is accepted, and we set $\boldsymbol{\alpha}^{(\ell+1)} = \tilde{\boldsymbol{\alpha}}^{(\ell+1)}$. After $I = 10^6$ initial burn-in iterations, the process is repeated until reaching $2I$ iterations to generate the samples.

To sample $p(\mathbf{D} \mid \mathbf{A}, \mathbf{Y}_T)$, starting from $\ell = I + 1$, values for each $\boldsymbol{\alpha}^{(\ell)}$ are generated according to:

$$\delta_{ii}^{(\ell)} \sim \Gamma\left(\kappa_i + \frac{T}{2}, \tau_i(\boldsymbol{\alpha}^{(\ell)}) + \frac{\zeta_i^*(\boldsymbol{\alpha}^{(\ell)})}{2}\right).$$

The variance of the structural shocks is calculated as $d_{ii}^{(\ell)} = 1/\delta_{ii}^{(\ell)}$ for $i = 1, 2, \cdots, n$, which are the diagonal elements of $\mathbf{D}^{(\ell)}$.

To sample the lagged structural coefficients $p(\mathbf{B} \mid \mathbf{A}, \mathbf{D}, \mathbf{Y}_T)$, values are drawn from:

$$b_i^{(\ell)} \sim N(\mathbf{m}_i^*(\boldsymbol{\alpha}^{(\ell)}), d_{ii}^{(\ell)}\mathbf{M}_i^*),$$

where:

$$\mathbf{m}_i^*(\boldsymbol{\alpha}^{(\ell)}) = (\tilde{\mathbf{X}}_i'\tilde{\mathbf{X}}_i)^{-1}(\tilde{\mathbf{X}}_i'\tilde{\mathbf{Y}}_i(\boldsymbol{\alpha}^{(\ell)})),$$

and:

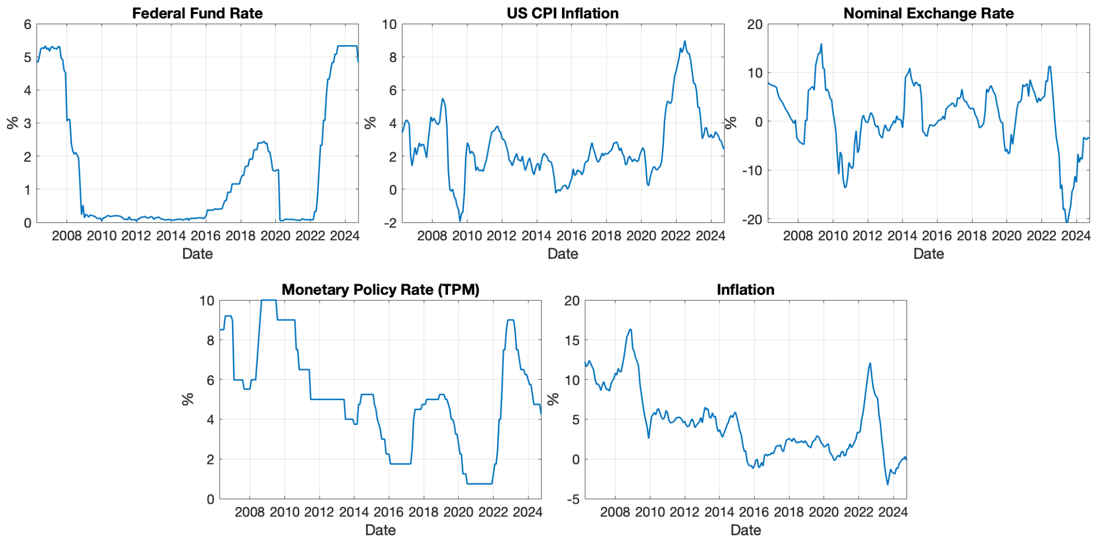
$$\mathbf{M}_i^* = (\tilde{\mathbf{X}}_i'\tilde{\mathbf{X}}_i)^{-1}.$$

Finally, matrix $\mathbf{B}^{(\ell)}$ is constructed using the rows $b_i^{(\ell)}$ for $i = 1, \ldots, n$. The definitions of $\tilde{\mathbf{X}}_i$ and $\tilde{\mathbf{Y}}_i$ are based on *Proposition 1* in Baumeister and Hamilton (2015), described in the appendix.

3.4 Data

The two main variables related to the pass-through effect are the nominal exchange rate (NER), represented by X_t, and a price variable, denoted as P_t. While the consumer price index (CPI) is commonly used, it is relevant to consider alternative measures, such as core inflation, price indices for specific product or service groups, or even an individual index associated with a specific product or service.

Figure 1: Sample of Model Variables



The analysis of exchange rate pass-through to prices is typically conducted using annual, quarterly, or monthly frequency data. In this study, all variables have a

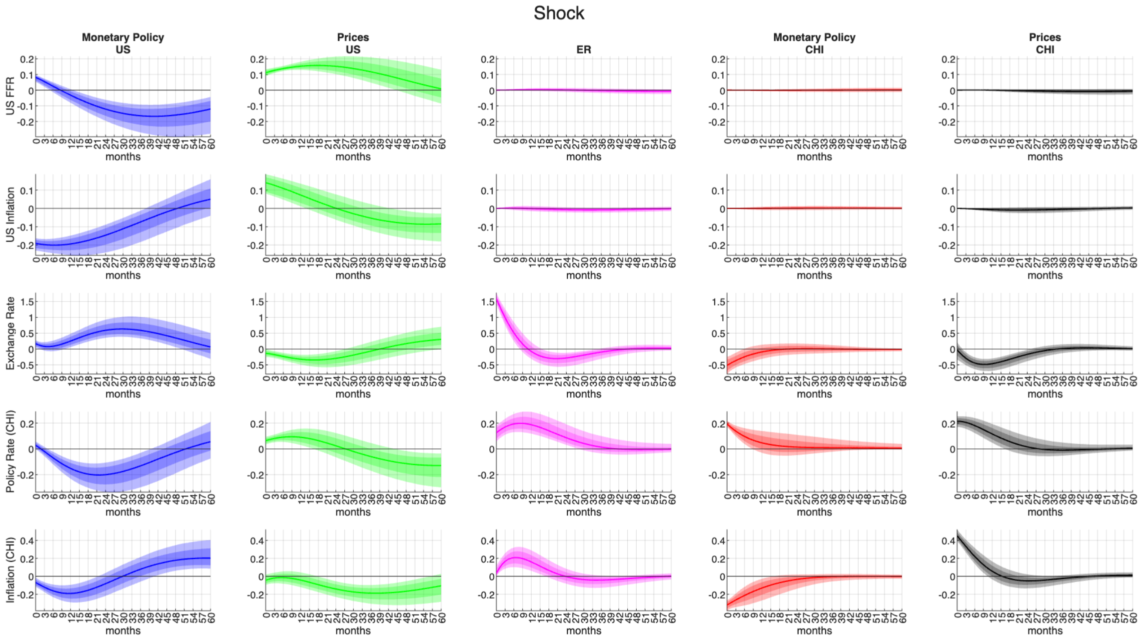


Figure 2: Enter Caption

monthly frequency. We use the average of the last monthly observation of the reference bid-ask nominal exchange rate reported by the Central Bank of Costa Rica (X_t).

The year-on-year variation of the NER is defined as:

$$x_t = 100 \cdot \left(\frac{X_t - X_{t-12}}{X_{t-12}} \right) \%, \tag{13}$$

while the year-on-year variation of the price variable, π_t, calculated analogously for P_t, is interpreted as the inflation rate. For Costa Rica's interest rate (i_t), we use the last monthly observation of the monetary policy rate (TPM).

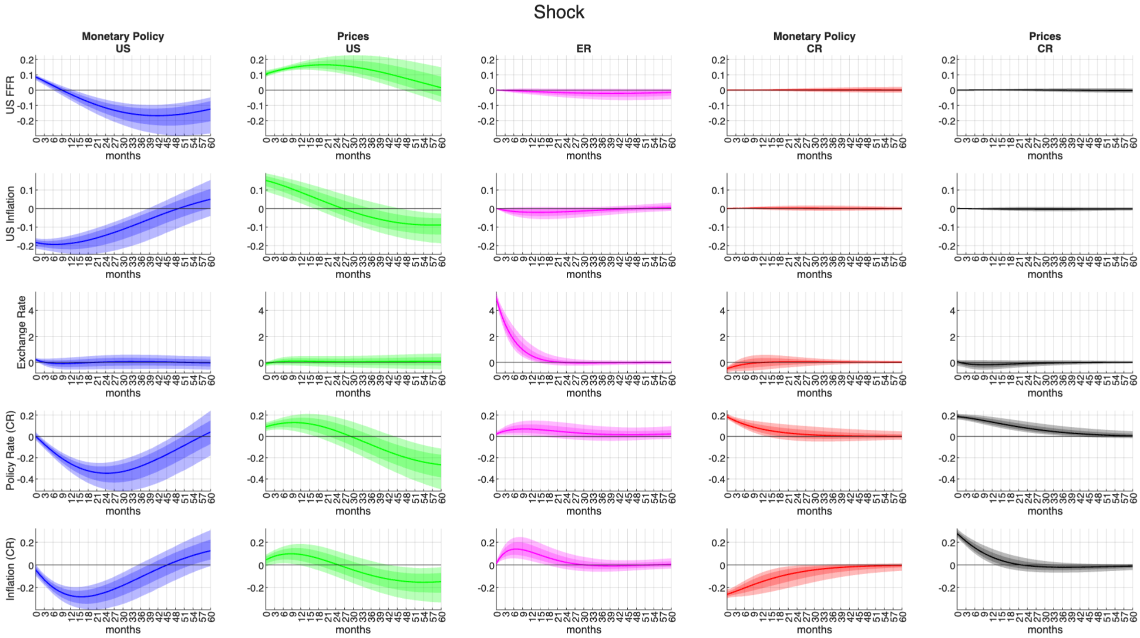
For the variables corresponding to the United States[10], the federal funds rate of the last day of the month (i_t^{USA}) and inflation (π_t^{USA}) are calculated based on the year-on-year variation of the consumer price index, excluding energy and food.

The sample covers the period from March 2006 to August 2024, which includes the beginning of the transition toward an inflation-targeting framework and a more flexible exchange rate regime in Costa Rica.

4 Results

The results presented derive from the estimation of the model discussed in the previous section. The point estimates correspond to the median of the *a posteriori* distributions of each parameter, including D and B. Likewise, through the relationship between equations (6) and (7), estimates of the reduced model are obtained. Credibility intervals for all parameters are calculated from these distributions using percentiles.

[10] Data is obtained from the Federal Reserve Economic Data (`https://fred.stlouisfed.org`).



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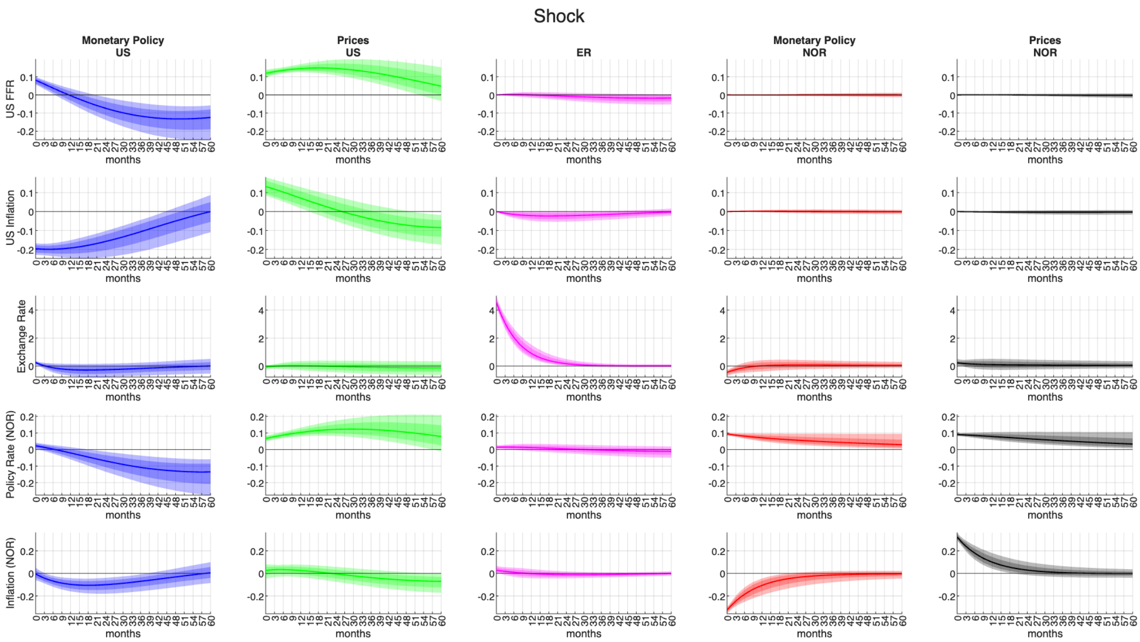

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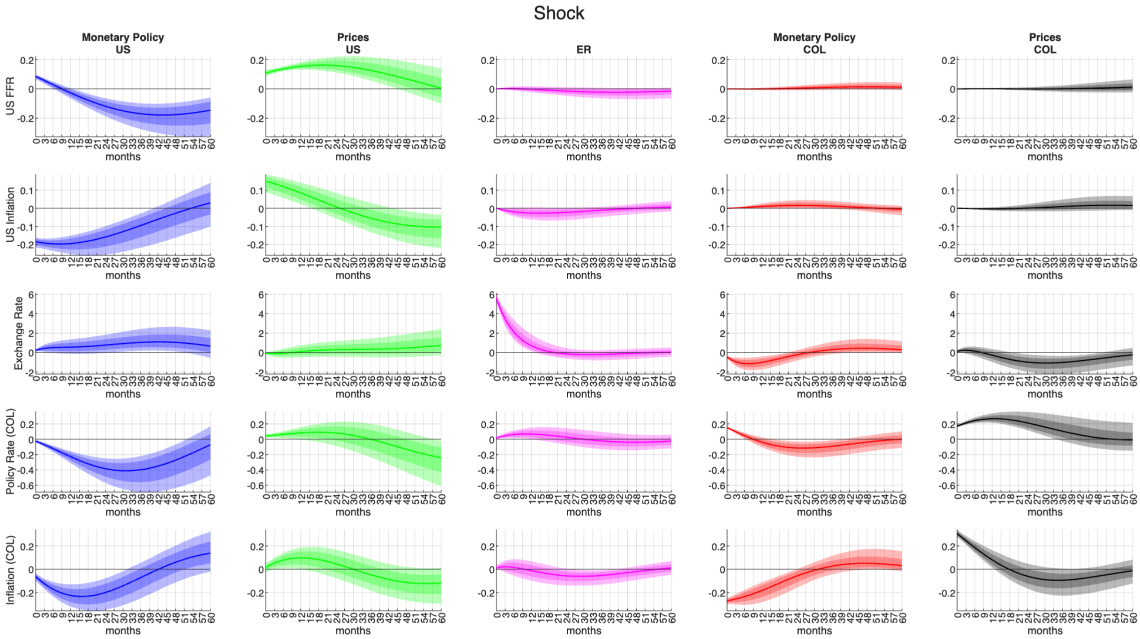

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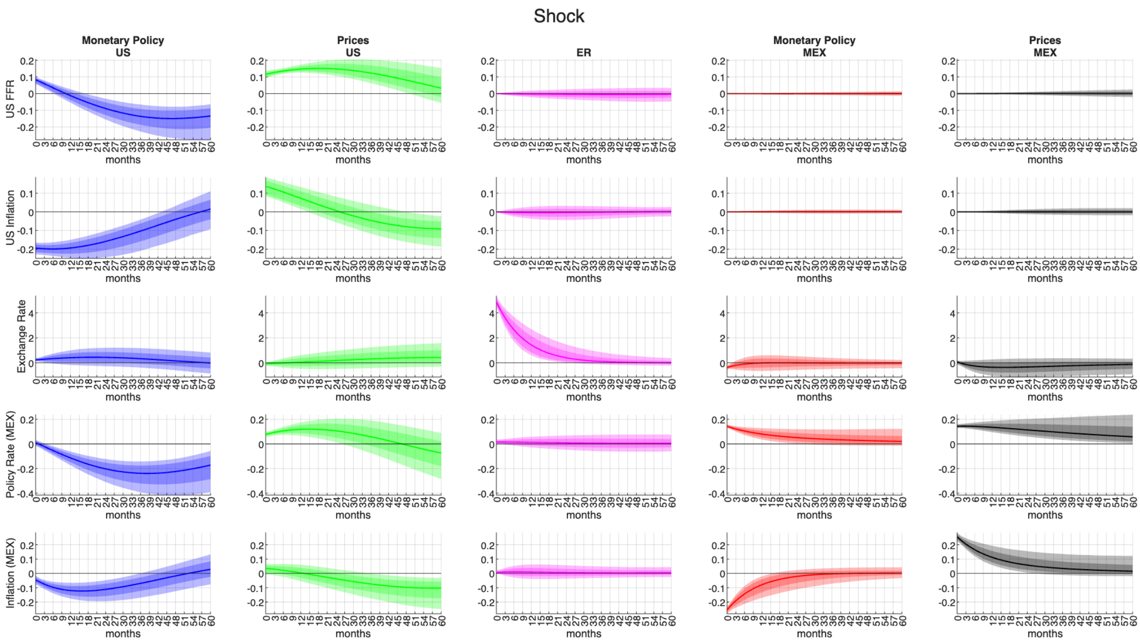


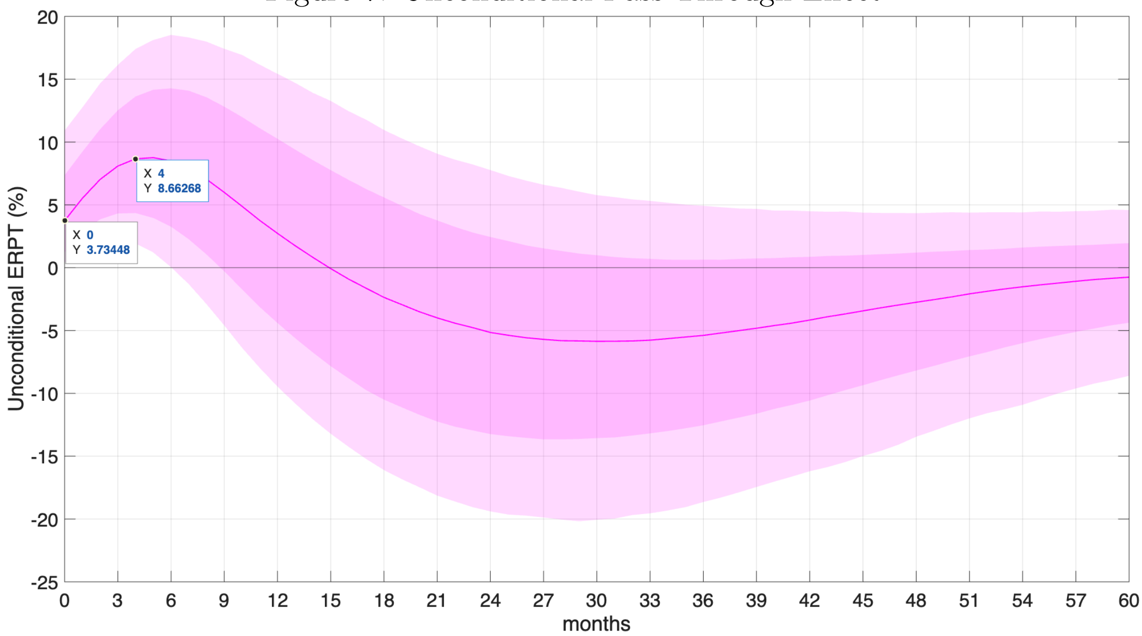
Figure 6: Enter Caption

The analysis focuses on the pass-through effect, the central theme of this study, and provides relevant insights into the Costa Rican economy, including the interaction between monetary policy, exchange rates, and inflation.

4.1 The Pass-Through Effect

Unconditional Pass-Through Effect Figure 7 shows the unconditional pass-through effect, defined as the response of prices to an unanticipated variation in the nominal exchange rate. This effect is measured as an elasticity, reflecting the percentage change in prices (%) in response to a percentage change in the nominal exchange rate.

Figure 7: Unconditional Pass-Through Effect

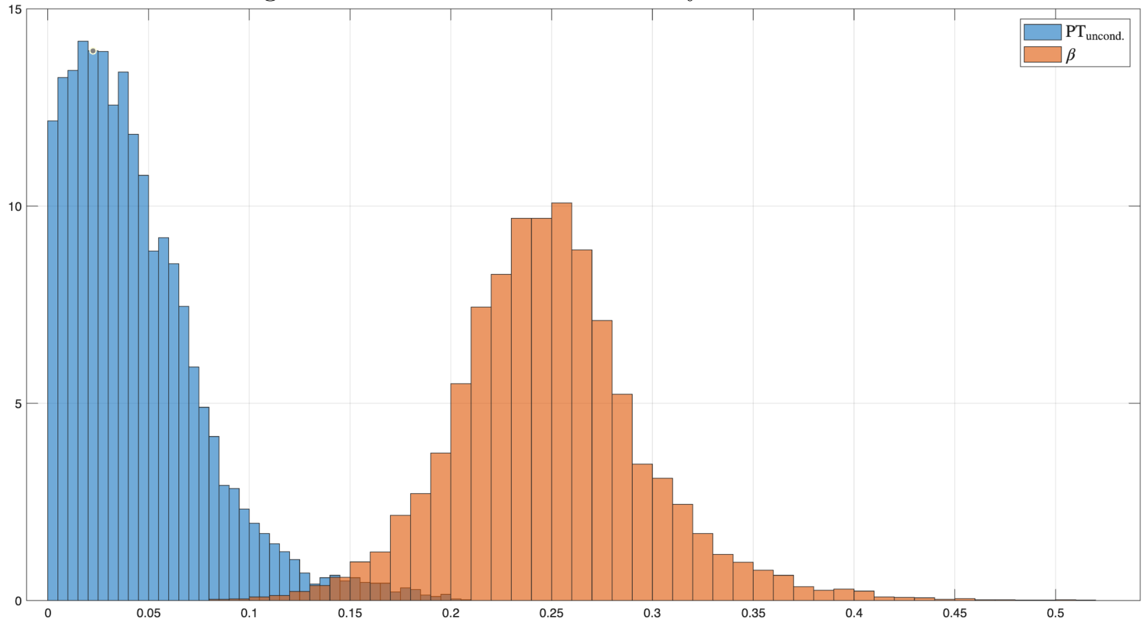


In the graph, the horizontal axis represents time (in months), while the vertical axis shows the estimated impact in percentage terms. The solid line corresponds to the median of the estimated *a posteriori* distribution, and the shaded areas indicate the 68% and 90% credibility intervals.

In the short term, the estimated effect is 4%, indicating a limited initial impact. However, this accumulated effect gradually grows and reaches significant values in the medium term, suggesting that an unanticipated depreciation of the nominal exchange rate generates cumulative inflationary pressure. From the sixth month onward, this impact becomes more evident but not significant at the 90% level. The widening of credibility intervals towards 24 months reflects greater uncertainty over longer horizons, although the general trend indicates a positive and increasing pass-through effect.

A possible explanation for the increasing uncertainty at horizons close to two years is the presence of asymmetric effects, meaning the existence of both a persistent and a more transitory response of the pass-through effect to different types of shocks. However, the estimation of an asymmetric pass-through effect is beyond the scope of this study.

Figure 8: Unconditional *versus* Systematic ERPT

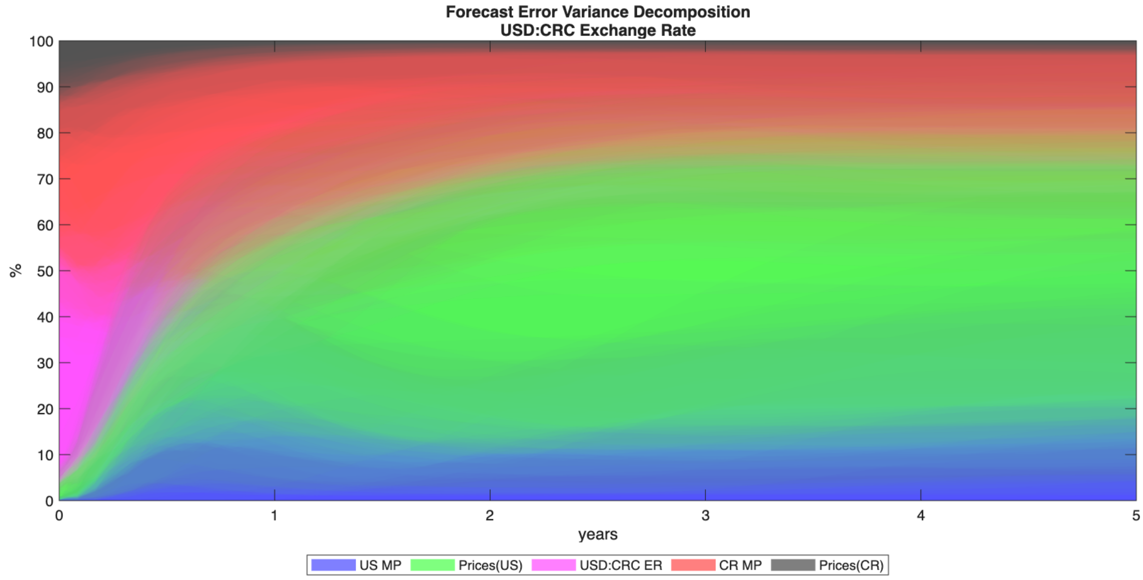


Systematic Pass-Through Effect The results for the systematic pass-through effect are based on a structural equation describing the relationship between inflation in Costa Rica (π_t) and a set of explanatory variables, including the nominal exchange rate (x_t), interest rate, and U.S. inflation (i_t^{EUA} and π_t^{EUA}), and the domestic monetary policy rate (i_t).

Figure 8 compares the posterior distributions of the unconditional exchange rate pass-through (ERPT) and the systematic ERPT coefficient, β. The unconditional ERPT, shown in blue, is tightly centered around 0.04, indicating that a 1% depreciation driven by an exchange rate shock raises inflation by roughly 0.04 percentage points. In contrast, the posterior distribution of the systematic ERPT, shown in orange, is centered near 0.25, more than six times larger. This substantial gap highlights how conventional ERPT estimates—based solely on exogenous exchange rate shocks—capture only a small part of the exchange rate's influence on inflation. By explicitly modeling the role of the exchange rate within the inflation determination process, the systematic ERPT measure incorporates the impact of both shock-driven and endogenous exchange rate movements, revealing a much stronger link between exchange rate dynamics and price changes. These results underscore the importance of distinguishing between these concepts when assessing the inflationary consequences of exchange rate movements.

4.2 Forecast Error Variance Decomposition

Figure 4.2 presents the forecast error variance decomposition of the USD/CRC nominal exchange rate over a five-year horizon. The decomposition attributes the share of exchange rate forecast variance to six structural shocks: U.S. monetary policy, U.S. prices, exchange rate (ER) shocks, Costa Rican monetary policy, Costa Rican prices, and other domestic factors. The colour bands represent the cumulative contribution of each shock over time, from the immediate impact to medium-term



horizons. The results reveal that ER shocks themselves account for only a small fraction of the exchange rate's variability, particularly beyond the first year. Instead, a substantial share is driven by foreign price shocks, domestic monetary policy, and other macroeconomic disturbances. This finding is critical for the interpretation of conventional exchange rate pass-through (ERPT) estimates. Standard approaches, which identify ERPT solely from exogenous ER shocks, capture only the small portion of exchange rate variation attributable to these shocks—potentially leading to severe underestimation of the true influence of the exchange rate on domestic prices. By showing that most exchange rate variability originates from systematic responses to broader macroeconomic conditions, the FEVD underscores the need for an ERPT framework that accounts for all sources of exchange rate movements.

4.3 Structural Equations

Estimating the model sheds light on the behavior of three key variables for the Costa Rican economy: the nominal exchange rate, the monetary policy rate, and inflation. Inflation has already been discussed in the context of the systematic exchange rate pass-through effect.

Structural equation for the nominal exchange rate Estimating the structural equation for the nominal exchange rate offers detailed insights into the causal relationships among the macroeconomic variables considered. The nominal exchange rate (x_t), measured as the year-over-year percentage change, is explained by the U.S. interest rate (i_t^{US}), U.S. inflation (π_t^{US}), the domestic monetary policy rate (i_t), and domestic inflation (π_t), along with lagged effects of these variables.

$$
\begin{aligned}
x_t = \underset{(0.3857)}{1.4309} \quad & + \underset{(0.3175)}{0.7980} i_t^{\text{US}} - \underset{(0.2129)}{0.3095} \pi_t^{\text{US}} - \underset{(0.4284)}{1.0538} i_t + \underset{(0.1912)}{0.7049} \pi_t \\
& - \underset{(0.3233)}{0.7867} i_{t-1}^{\text{US}} + \underset{(0.2246)}{0.1351} \pi_{t-1}^{\text{US}} + \underset{(0.0257)}{0.9148} x_{t-1} + \underset{(0.4302)}{0.7191} i_{t-1} - \underset{(0.1946)}{0.5320} \pi_{t-1} + \underset{(0.6708)}{1.9950} \epsilon_t^x
\end{aligned}
$$

The constant term of 1.4309 indicates an average depreciation trend of the nominal exchange rate in the absence of changes in explanatory variables. This may reflect structural long-term dynamics within the Costa Rican economy.

Regarding external variables, an increase in the U.S. monetary policy rate significantly raises the nominal exchange rate. Specifically, a one percentage-point increase in i_t^{US} leads to a 0.798 percentage-point rise in the nominal exchange rate, highlighting the influence of U.S. monetary policy on currency value and exchange rates. Conversely, higher U.S. inflation (π_t^{US}) reduces the nominal exchange rate by 0.31 percentage points, possibly reflecting improvements in the relative competitiveness of U.S. goods.

Domestic variables are also crucial determinants. An increase in the domestic interest rate reduces the nominal exchange rate by 1.05 percentage points, suggesting higher domestic rates attract foreign capital inflows, strengthening the local currency. Conversely, higher domestic inflation leads to nominal exchange rate depreciation, increasing by 0.70 percentage points, reflecting the adverse impact of inflation on purchasing power and currency competitiveness.

Lagged effects of these variables are also significant. The previous period's U.S. interest rate (i_{t-1}^{US}) negatively influences the current exchange rate, whereas lagged U.S. inflation (π_{t-1}^{US}) has a positive impact. For domestic variables, the previous period's interest rate (i_{t-1}) significantly positively impacts the current exchange rate, while lagged inflation (π_{t-1}) negatively affects it, suggesting an adjustment mechanism in exchange rate dynamics.

Finally, the lagged nominal exchange rate (x_{t-1}) coefficient (0.9148) indicates high persistence, meaning past exchange rate shocks significantly influence current values, reflecting gradual adjustment dynamics.

Together, these results underscore the importance of considering both internal and external factors in Costa Rica's nominal exchange rate dynamics. The interactions among interest rates, inflation, and lagged effects reveal complex causal structures crucial for formulating monetary and exchange rate stability policies.

Structural equation for monetary policy Estimating the structural equation for Costa Rica's monetary policy rate (i_t) provides comprehensive insights into determinants affecting its dynamics within a framework prioritizing inflation control, as established by the legal mandate. The results demonstrate significant influences of other variables through inflation expectations and common factors between the Costa Rican and U.S. economies. The estimated equation is:

$$\begin{aligned} i_t = \underset{(0.0997)}{-0.1383} \quad & + \underset{(0.1606)}{0.5986} i_t^{\text{US}} + \underset{(0.0370)}{0.0392} \pi_t^{\text{US}} + \underset{(0.0223)}{0.0620} x_t + \underset{(0.1701)}{0.3840} \pi_t \\ & - \underset{(0.1579)}{0.6067} i_{t-1}^{\text{US}} - \underset{(0.0487)}{0.0248} \pi_{t-1}^{\text{US}} - \underset{(0.0263)}{0.0546} x_{t-1} + \underset{(0.0216)}{0.9932} i_{t-1} - \underset{(0.1642)}{0.3543} \pi_{t-1} - \underset{(0.2538)}{0.4400} \epsilon_t^i \end{aligned}$$

Among external variables, the U.S. monetary policy rate (i_t^{US}) positively influences the domestic rate, with a 0.5986 coefficient, emphasizing economic interdependence and global financial conditions' impact on Costa Rican monetary policy. Similarly, U.S. inflation (π_t^{US}) positively influences domestic inflation expectations, albeit to a lesser extent (0.0392 coefficient).

Domestically, inflation (π_t) significantly impacts the monetary policy rate (0.3840 coefficient), reinforcing Costa Rica's primary focus on inflation control. Additionally, the nominal exchange rate (x_t) positively impacts monetary policy decisions

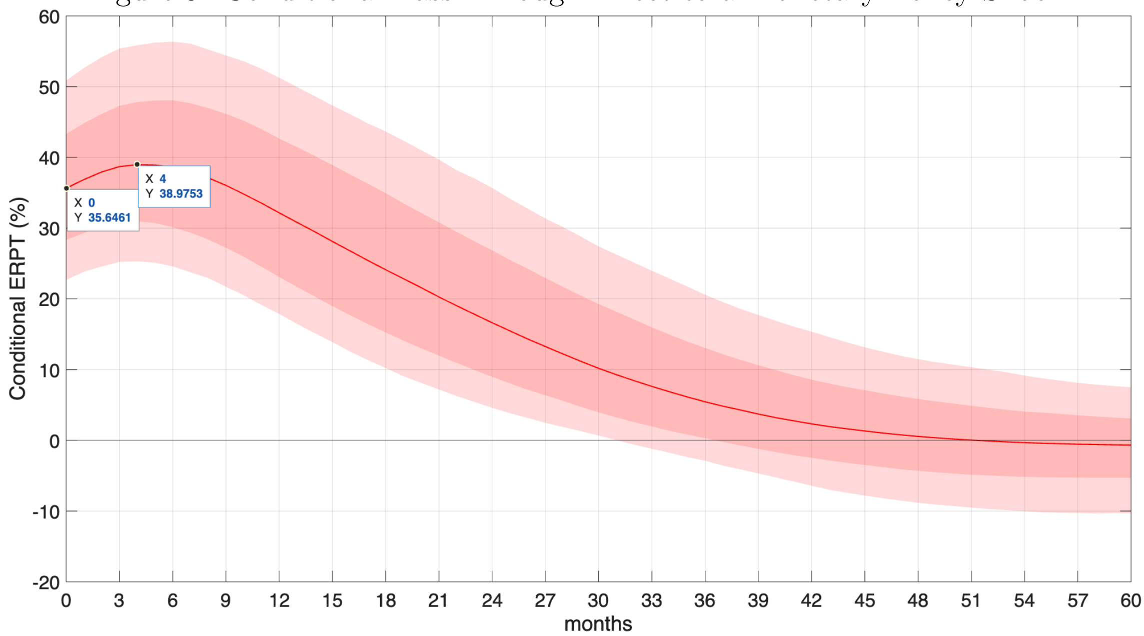
(0.0620 coefficient), reflecting the relevance of inflation expectations linked to currency depreciation.

Lagged variables illustrate the persistent dynamics of monetary policy. The previous U.S. interest rate (i_{t-1}^{US}) negatively affects the current domestic rate, offsetting contemporaneous effects, highlighting rapid shock transmission. Similarly, contemporaneous effects from the exchange rate and domestic inflation are temporary.

Overall, these findings emphasize monetary policy complexity in Costa Rica, highlighting inflation control as the primary objective while considering the significant influence of exchange rates, external interest rates, and international inflation conditions. This structural framework enhances the understanding of economic interactions between Costa Rica and the U.S., underscoring expectations and common factors within an increasingly interconnected economic environment.

Conditional Pass-Through Effect to a Monetary Policy Shock Figure 9 illustrates the conditional pass-through effect in response to a monetary policy shock, evaluating how a change in the monetary policy rate affects inflation through its impact on the nominal exchange rate. This effect is measured in terms of elasticity, so the shape of the impulse-response function is determined by the ratio between the response of inflation to the monetary policy shock (numerator) and the response of the exchange rate to the same shock (denominator).

Figure 9: Conditional Pass-Through Effect to a Monetary Policy Shock



Initially, the effect is significant, with an elasticity close to 150%, indicating a considerable immediate impact. As months pass, the effect gradually decreases and stabilizes, with a slight upward trend in the long run. This analysis highlights monetary policy as a key channel in the transmission of exchange rate fluctuations to prices.

5 Conclusions

This paper revisits the measurement of exchange rate pass-through (ERPT) in small open economies, using Costa Rica as a case study. Standard approaches, which identify ERPT from exogenous exchange rate shocks, yield an unconditional short-term semi-elasticity of about 4%, rising modestly over longer horizons. While desirable from a price stability perspective, such estimates fail to capture the broader role of the exchange rate in domestic inflation dynamics.

Our analysis shows that exchange rate shocks account for only a small fraction of the USD/CRC exchange rate's variance. Most fluctuations are systematically linked to other macroeconomic forces, including monetary policy and domestic and foreign price developments. By explicitly modelling the inflation determination process within a structural VAR, we derive a measure of *systematic* ERPT that incorporates the effects of all exchange rate movements, both shock-driven and endogenous. This measure is over six times larger than the unconditional estimate, with a 1% year-on-year depreciation associated with a 0.25 percentage point increase in inflation.

These results reconcile the apparent puzzle between low conventional ERPT coefficients and the widespread perception that exchange rate movements strongly influence inflation. They also demonstrate that the exchange rate, despite its comovement with prices, is an ineffective instrument for direct inflation control. For policymakers in small open economies, this implies that ERPT assessments must account for the underlying sources of exchange rate variation and the broader macroeconomic environment. Failing to do so risks understating the exchange rate's relevance for inflation dynamics and misjudging the transmission channels of monetary policy.

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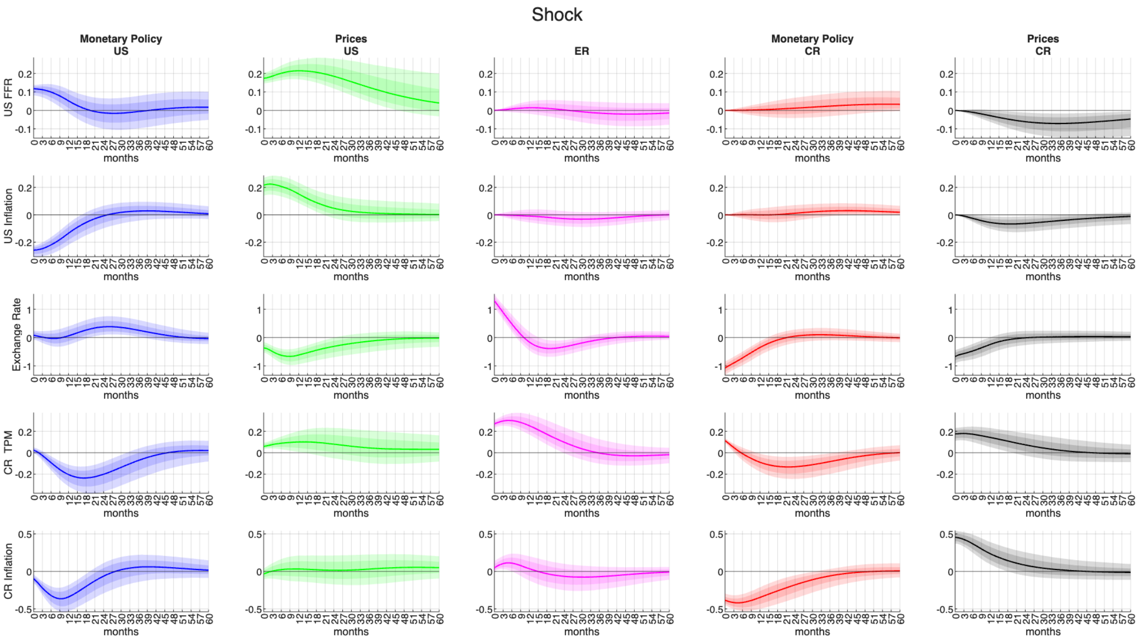
A Impulse Response Functions and the Series of Shocks

This section analyzes the economic dynamics captured by the model through impulse response functions and the estimation of structural shocks. The impulse response functions allow us to evaluate the interaction between key macroeconomic variables in response to different shocks, providing a detailed view of transmission and adjustment mechanisms. Meanwhile, the estimation of structural shocks offers a historical perspective on events that have affected the Costa Rican economy, identifying specific patterns during periods of instability or significant changes in external and internal conditions. Both analyses are fundamental to understanding economic dynamics and the effectiveness of economic policy in a context of international interdependence.

A.1 Impulse Response Functions

This section summarizes the main results derived from the impulse response functions estimated from the model. These functions analyze the adjustment dynamics of key macroeconomic variables in response to different types of structural shocks, also considering the 68% credibility intervals (darker shaded area) and the 90% credibility intervals (lighter shaded area). The credibility intervals were calculated using a random sample of 10,000 parameter sets from the *a posteriori* distribution, ensuring robustness in the estimates.

Figure 10: Impulse Response Functions of the Model



Note: The shaded area represents the 68% confidence interval (darker) and the 90% confidence interval (lighter). The credible intervals are obtained by recalculating the impulse response functions for a random sample of 10,000 parameter sets from the *a posteriori* distribution.

- **Shocks to U.S. Monetary Policy:** A positive shock to the U.S. monetary policy rate generates an immediate and significant effect on the federal funds rate, close to 20 basis points. This effect persists over several months, although with decreasing magnitude. Regarding domestic prices and the nominal exchange rate, the response is more moderate and materializes with some lag, reflecting the transmission of external monetary policy through financial and expectations channels.

- **Shocks to U.S. Prices:** An increase in U.S. inflation has significant effects on domestic inflation, though with an initial lag, reflecting Costa Rica's sensitivity to international price changes. Meanwhile, the impact on the domestic monetary policy rate is positive but smaller in magnitude, highlighting how external inflation expectations indirectly influence local monetary policy.

- **Shocks to the Nominal Exchange Rate:** A positive shock to the nominal exchange rate generates an immediate response in domestic inflation, highlighting the pass-through effect of exchange rate movements on domestic prices. This impact gradually dissipates over time, with full adjustment occurring within approximately 12 to 18 months. Additionally, the response of domestic monetary policy is significant and positive, indicating the use of the interest rate as a tool to mitigate inflationary effects resulting from exchange rate depreciation.

- **Shocks to Domestic Monetary Policy:** An increase in the domestic monetary policy rate has a contractionary effect on inflation, consistent with the monetary policy focus on price control. Additionally, this shock leads to an immediate appreciation of the nominal exchange rate, suggesting a stabilizing effect on exchange rate expectations. The magnitude of these effects gradually decreases, converging to equilibrium in the medium term.

- **Shocks to Domestic Prices:** An increase in domestic inflation triggers an immediate response in the monetary policy rate, with a positive and significant adjustment to contain inflationary pressures. This shock also impacts the nominal exchange rate, causing an initial depreciation that gradually corrects, demonstrating the transmission mechanisms between prices and the exchange rate in the Costa Rican economy.

In summary, the impulse response functions highlight the interdependence between the Costa Rican and U.S. economies, as well as the effectiveness of domestic monetary policy in stabilizing key macroeconomic variables in response to different types of structural shocks. These results align with theoretical transmission channels and reinforce the importance of designing policies that consider both internal and external factors.

A.2 Structural Shocks

Figure 11 presents the time series of structural shocks estimated from the model. These series reflect the dynamics of the five structural shocks considered: U.S. monetary policy, U.S. prices, the nominal exchange rate, domestic monetary policy, and domestic prices. The credibility intervals, represented by shaded areas, correspond

Figure 11: Credibility Intervals of Observed Shocks

to confidence levels of 68% (dark gray) and 90% (light gray), allowing for a robust assessment of the uncertainty associated with these estimates.

Below, the main patterns observed in each series are described:

- **U.S. Monetary Policy:** Shocks associated with U.S. monetary policy show greater volatility during the periods of the global financial crisis (2008-2009) and the COVID-19 pandemic (2020-2021). These fluctuations reflect significant adjustments made by the Federal Reserve in its interest rates in response to exceptional economic conditions. In more recent periods, shocks tend to stabilize, indicating a return to more predictable patterns.

- **U.S. Prices:** Shocks to U.S. prices remain relatively contained throughout the sample, with observable peaks during periods of greater economic uncertainty, such as in 2008 and during the pandemic. These shocks align with changes in international prices and global inflationary conditions that indirectly impact the Costa Rican economy.

- **Nominal Exchange Rate:** Structural shocks to the nominal exchange rate are more pronounced during periods of macroeconomic instability, particularly around 2008-2009 and 2014-2015. These events may be associated with fluctuations in capital flows, external shocks, and exchange rate policy adjustments. Credibility intervals are wider during these periods, reflecting greater uncertainty in the estimates.

- **Domestic Monetary Policy:** Shocks associated with domestic monetary policy show significant variability during periods of economic adjustment, especially in 2008 and 2020. This reflects monetary policy responses to external and internal events that impacted Costa Rica's economic conditions. Over time, shocks tend to converge towards values closer to zero, suggesting a return to a more stable economic environment.

- **Domestic Prices:** Structural shocks to domestic prices exhibit patterns consistent with local inflation dynamics, showing greater volatility in 2008 and a rebound during 2020-2021, coinciding with the pandemic's impacts. These shocks are key to understanding local inflationary pressures and their effects on stabilization policies.

Overall, the estimated structural shocks reflect the interaction between external and internal factors in the Costa Rican economy, with patterns consistent with significant global and domestic events throughout the analyzed period. The inclusion of credibility intervals allows for a more precise identification of periods of higher uncertainty and highlights the robustness of the model estimates. These results complement the main analysis and provide a detailed view of the underlying determinants of key macroeconomic variable dynamics.

B The Matrix H

The attached matrix corresponds to H, which is obtained by multiplying the inverse of matrix A by the square root of D, that is:

$$H = A^{-1}\sqrt{D}.$$

$$H = \begin{pmatrix}
-\frac{\sigma^{i^{\text{EUA}}}}{\theta^i\theta^\pi-1} & -\frac{\sigma^{\pi^{\text{EUA}}}\theta^\pi}{\theta^i\theta^\pi-1} & 0 & 0 & 0 \\
-\frac{\sigma^{i^{\text{EUA}}}\theta^i}{\theta^i\theta^\pi-1} & -\frac{\sigma^{\pi^{\text{EUA}}}}{\theta^i\theta^\pi-1} & 0 & 0 & 0 \\
\frac{\sigma^{i^{\text{EUA}}}\left(\kappa^i+\alpha\eta^i+\kappa^\pi\theta^i+\phi\xi^i+\alpha\eta^\pi\theta^i+\eta^i\gamma\phi-\gamma\kappa^i\tau+\alpha\tau\xi^i+\phi\theta^i\xi^\pi+\eta^\pi\gamma\phi\theta^i-\gamma\kappa^\pi\tau\theta^i+\alpha\tau\theta^i\xi^\pi\right)}{(\theta^i\theta^\pi-1)(\alpha\beta+\delta\phi+\gamma\tau+\beta\gamma\phi+\alpha\delta\tau-1)} & \frac{\sigma^{\pi^{\text{EUA}}}\left(\kappa^\pi+\alpha\eta^\pi+\kappa^i\theta^\pi+\phi\xi^\pi+\alpha\eta^i\theta^\pi+\eta^\pi\gamma\phi-\gamma\kappa^\pi\tau+\alpha\tau\xi^\pi+\phi\theta^\pi\xi^i+\eta^i\gamma\phi\theta^\pi-\gamma\kappa^i\tau\theta^\pi+\alpha\tau\theta^\pi\xi^i\right)}{(\theta^i\theta^\pi-1)(\alpha\beta+\delta\phi+\gamma\tau+\beta\gamma\phi+\alpha\delta\tau-1)} & -\frac{\sigma^x(1-\gamma\tau)}{\alpha\beta+\delta\phi+\gamma\tau+\beta\gamma\phi+\alpha\delta\tau-1} & -\frac{\sigma^i(\phi+\alpha\tau)}{\alpha\beta+\delta\phi+\gamma\tau+\beta\gamma\phi+\alpha\delta\tau-1} & -\frac{\sigma^\pi(\alpha+\gamma\phi)}{\alpha\beta+\delta\phi+\gamma\tau+\beta\gamma\phi+\alpha\delta\tau-1} \\
\frac{\sigma^{i^{\text{EUA}}}\left(\xi^i+\eta^i\gamma+\delta\kappa^i+\theta^i\xi^\pi+\beta\gamma\kappa^i-\alpha\beta\xi^i+\eta^\pi\gamma\theta^i+\delta\kappa^\pi\theta^i+\alpha\delta\eta^i+\alpha\delta\eta^\pi\theta^i+\beta\gamma\kappa^\pi\theta^i-\alpha\beta\theta^i\xi^\pi\right)}{(\theta^i\theta^\pi-1)(\alpha\beta+\delta\phi+\gamma\tau+\beta\gamma\phi+\alpha\delta\tau-1)} & \frac{\sigma^{\pi^{\text{EUA}}}\left(\xi^\pi+\eta^\pi\gamma+\delta\kappa^\pi+\theta^\pi\xi^i+\beta\gamma\kappa^\pi-\alpha\beta\xi^\pi+\eta^i\gamma\theta^\pi+\delta\kappa^i\theta^\pi+\alpha\delta\eta^\pi+\alpha\delta\eta^i\theta^\pi+\beta\gamma\kappa^i\theta^\pi-\alpha\beta\theta^\pi\xi^i\right)}{(\theta^i\theta^\pi-1)(\alpha\beta+\delta\phi+\gamma\tau+\beta\gamma\phi+\alpha\delta\tau-1)} & -\frac{\sigma^x(\delta+\beta\gamma)}{\alpha\beta+\delta\phi+\gamma\tau+\beta\gamma\phi+\alpha\delta\tau-1} & -\frac{\sigma^i(1-\alpha\beta)}{\alpha\beta+\delta\phi+\gamma\tau+\beta\gamma\phi+\alpha\delta\tau-1} & -\frac{\sigma^\pi(\gamma+\alpha\delta)}{\alpha\beta+\delta\phi+\gamma\tau+\beta\gamma\phi+\alpha\delta\tau-1} \\
\frac{\sigma^{i^{\text{EUA}}}\left(\eta^i+\beta\kappa^i+\eta^\pi\theta^i+\tau\xi^i-\delta\eta^i\phi+\beta\kappa^\pi\theta^i+\delta\kappa^i\tau+\beta\phi\xi^i+\tau\theta^i\xi^\pi-\delta\eta^\pi\phi\theta^i+\delta\kappa^\pi\tau\theta^i+\beta\phi\theta^i\xi^\pi\right)}{(\theta^i\theta^\pi-1)(\alpha\beta+\delta\phi+\gamma\tau+\beta\gamma\phi+\alpha\delta\tau-1)} & \frac{\sigma^{\pi^{\text{EUA}}}\left(\eta^\pi+\beta\kappa^\pi+\eta^i\theta^\pi+\tau\xi^\pi-\delta\eta^\pi\phi+\beta\kappa^i\theta^\pi+\delta\kappa^\pi\tau+\beta\phi\xi^\pi+\tau\theta^\pi\xi^i-\delta\eta^i\phi\theta^\pi+\delta\kappa^i\tau\theta^\pi+\beta\phi\theta^\pi\xi^i\right)}{(\theta^i\theta^\pi-1)(\alpha\beta+\delta\phi+\gamma\tau+\beta\gamma\phi+\alpha\delta\tau-1)} & -\frac{\sigma^x(\beta+\delta\tau)}{\alpha\beta+\delta\phi+\gamma\tau+\beta\gamma\phi+\alpha\delta\tau-1} & -\frac{\sigma^i(\tau+\beta\phi)}{\alpha\beta+\delta\phi+\gamma\tau+\beta\gamma\phi+\alpha\delta\tau-1} & -\frac{\sigma^\pi(1-\delta\phi)}{\alpha\beta+\delta\phi+\gamma\tau+\beta\gamma\phi+\alpha\delta\tau-1}
\end{pmatrix}$$

This matrix represents the impulse response functions of the model, allowing the analysis of the dynamics of endogenous variables in response to structural shocks. In the main text, H is mentioned as the central component for interpreting dynamic effects, as it encapsulates both the structural properties of the model and the magnitude of the shocks. The detailed structure of H, as presented here, is key to assessing how relationships between economic variables adjust over time.

C Proof That the Systematic Pass-Through Effect is Greater Than the Unconditional Pass-Through Effect

Assuming that all parameters δ, τ, and γ are nonzero, and considering that the parameter β is adjusted by a factor generally greater than 1, obtained as the ratio between the nominal exchange rate and the consumer price index, it can be demonstrated that the systematic pass-through effect is greater than the unconditional pass-through effect.

Let us consider the expression for the conditional pass-through effect:

$$\mathrm{ET}_0^x = \frac{\beta + \delta\tau}{1 - \gamma\tau},$$

where it is assumed that $\gamma > 0$ and $\tau < 0$. Since $\gamma\tau < 0$, then $1-\gamma\tau > 1$. Therefore, it follows that:

$$\frac{\beta + \delta\tau}{1 - \gamma\tau} < \beta + \delta\tau < \beta.$$

Additionally, given that $\delta > 0$ and $\tau < 0$, it implies that $\delta\tau < 0$, ensuring that $\beta + \delta\tau < \beta$. Finally, since β is adjusted by a factor $\upsilon > 1$, this is used to make β comparable to the unconditional pass-through effect. Thus, the conditional pass-through effect turns out to be greater than the unconditional one, considering that:

$$\beta < \beta\upsilon.$$

In summary, incorporating the adjustments related to υ, it is demonstrated that the systematic pass-through effect exceeds the unconditional one under the given conditions.

D How to Obtain the Matrix Form

We start from the five equations that define our model:

$$i_t^{\mathrm{EUA}} = c^{i^{\mathrm{EUA}}} + \theta^{\pi}\pi_t^{\mathrm{EUA}} + f_{i^{\mathrm{EUA}}}(\mathfrak{F}_{t-1}) + \sigma^{i^{\mathrm{EUA}}}\epsilon_t^{i^{\mathrm{EUA}}} \tag{4}$$
$$\pi_t^{\mathrm{EUA}} = c^{\pi^{\mathrm{EUA}}} + \theta^{i} i_t^{\mathrm{EUA}} + f_{\pi^{\mathrm{EUA}}}(\mathfrak{F}_{t-1}) + \sigma^{\pi^{\mathrm{EUA}}}\epsilon_t^{\pi^{\mathrm{EUA}}} \tag{5}$$
$$x_t = c^x + \kappa^i i_t^{\mathrm{EUA}} + \kappa^{\pi}\pi_t^{\mathrm{EUA}} + \phi i_t + \alpha\pi_t + f_x(\mathfrak{F}_{t-1}) + \sigma^x\epsilon_t^x \tag{2}$$
$$i_t = c^i + \xi^i i_t^{\mathrm{EUA}} + \xi^{\pi}\pi_t^{\mathrm{EUA}} + \delta x_t + \gamma\pi_t + f_i(\mathfrak{F}_{t-1}) + \sigma^i\epsilon_t^i \tag{3}$$
$$\pi_t = c^{\pi} + \eta^i i_t^{\mathrm{EUA}} + \eta^{\pi}\pi_t^{\mathrm{EUA}} + \beta x_t + \tau i_t + f_{\pi}(\mathfrak{F}_{t-1}) + \sigma^{\pi}\epsilon_t^{\pi} \tag{1}$$

We move all contemporary variables to the left-hand side:

$$\begin{aligned}
i_t^{\text{EUA}} - \theta^{\pi}\pi_t^{\text{EUA}} &= c^{i^{\text{EUA}}} + f_{i^{\text{EUA}}}(\mathfrak{F}_{t-1}) + \sigma^{i^{\text{EUA}}}\epsilon_t^{i^{\text{EUA}}} \\
\pi_t^{\text{EUA}} - \theta^{i} i_t^{\text{EUA}} &= c^{\pi^{\text{EUA}}} + f_{\pi^{\text{EUA}}}(\mathfrak{F}_{t-1}) + \sigma^{\pi^{\text{EUA}}}\epsilon_t^{\pi^{\text{EUA}}} \\
x_t - \kappa^{i} i_t^{\text{EUA}} - \kappa^{\pi}\pi_t^{\text{EUA}} - \phi i_t - \alpha\pi_t &= c^{x} + f_{x}(\mathfrak{F}_{t-1}) + \sigma^{x}\epsilon_t^{x} \\
i_t - \xi^{i} i_t^{\text{EUA}} - \xi^{\pi}\pi_t^{\text{EUA}} - \delta x_t - \gamma\pi_t &= c^{i} + f_{i}(\mathfrak{F}_{t-1}) + \sigma^{i}\epsilon_t^{i} \\
\pi_t - \eta^{i} i_t^{\text{EUA}} - \eta^{\pi}\pi_t^{\text{EUA}} - \beta x_t - \tau i_t &= c^{\pi} + f_{\pi}(\mathfrak{F}_{t-1}) + \sigma^{\pi}\epsilon_t^{\pi}
\end{aligned}$$

To obtain the desired matrix form:

$$\begin{bmatrix} 1 & -\theta^{\pi} & 0 & 0 & 0 \\ -\theta^{i} & 1 & 0 & 0 & 0 \\ -\kappa^{i} & -\kappa^{\pi} & 1 & -\phi & -\alpha \\ -\xi^{i} & -\xi^{\pi} & -\delta & 1 & -\gamma \\ -\eta^{i} & -\eta^{\pi} & -\beta & -\tau & 1 \end{bmatrix} \begin{pmatrix} i_t^{\text{EUA}} \\ \pi_t^{\text{EUA}} \\ x_t \\ i_t \\ \pi_t \end{pmatrix} = \begin{pmatrix} c^{i^{\text{EUA}}} \\ c^{\pi^{\text{EUA}}} \\ c^{x} \\ c^{i} \\ c^{\pi} \end{pmatrix} + \begin{pmatrix} f_{i^{EUA}}(\mathfrak{F}_{t-1}) \\ f_{\pi^{EUA}}(\mathfrak{F}_{t-1}) \\ f_{x}(\mathfrak{F}_{t-1}) \\ f_{i}(\mathfrak{F}_{t-1}) \\ f_{\pi}(\mathfrak{F}_{t-1}) \end{pmatrix} + \begin{pmatrix} \sigma^{i^{EUA}}\epsilon_t^{i^{\text{EUA}}} \\ \sigma^{\pi^{EUA}}\epsilon_t^{\pi^{\text{EUA}}} \\ \sigma^{x}\epsilon_t^{x} \\ \sigma^{i}\epsilon_t^{i} \\ \sigma^{\pi}\epsilon_t^{\pi} \end{pmatrix}$$

E Metropolis-Hastings Algorithm for Estimating a Bayesian SVAR Model

In this appendix, we describe the use of the Metropolis-Hastings algorithm for estimating a structural vector autoregression (SVAR) model under a Bayesian approach.

The Metropolis-Hastings algorithm is a Markov chain Monte Carlo sampling method used to approximate complex probability distributions. In the context of a Bayesian SVAR model, it is employed to obtain samples from the posterior distribution of the model's structural parameters.

Metropolis-Hastings Algorithm. The procedure can be described as follows:

Algorithm 1 Metropolis-Hastings Algorithm for a Bayesian SVAR Model

```
Initialize the parameters θ^(0) with an initial value.
for i = 1 to N (number of iterations) do
    Propose a new value θ* from a proposal distribution q(θ*|θ^(i−1)).
    Compute the acceptance probability:
        α = min(1, p(y|θ*)p(θ*)q(θ^(i−1)|θ*) / (p(y|θ^(i−1))p(θ^(i−1))q(θ*|θ^(i−1)))),
    where p(y|θ) is the likelihood and p(θ) is the prior distribution.
    Generate u ∼ Uniform(0, 1).
    if u ≤ α then
        Accept θ* and set θ^(i) = θ*.
    else
        Reject θ* and set θ^(i) = θ^(i−1).
    end if
end for
```

$$\alpha = \min\left(1, \frac{p(y|\theta^*)p(\theta^*)q(\theta^{(i-1)}|\theta^*)}{p(y|\theta^{(i-1)})p(\theta^{(i-1)})q(\theta^*|\theta^{(i-1)})}\right),$$

The Metropolis-Hastings algorithm is a powerful tool for estimating SVAR models within a Bayesian framework, allowing inferences on structural parameters based on complex posterior distributions.

F Proposition 1 from Baumeister and Hamilton (2015)

The components of the Bayesian posterior distributions can be conveniently characterized through regressions on augmented datasets defined as:

$$\underset{[(T+k)\times 1]}{\tilde{\mathbf{Y}}_{i}} = \left[\begin{array}{ccccc} \mathbf{y}_1'\mathbf{a}_i & \cdots & \mathbf{y}_T'\mathbf{a}_i & \mathbf{m}_i'\mathbf{P}_i \end{array}\right]',$$
$$\underset{[(T+k)\times k]}{\tilde{\mathbf{X}}_i} = \left[\begin{array}{cccc} \mathbf{x}_0' & \cdots & \mathbf{x}_{T-1}' & \mathbf{P}_i \end{array}\right]',$$

where $\mathbf{P}_i$ is the Cholesky factor of $\mathbf{M}_i^{-1} = \mathbf{P}_i\mathbf{P}_i'$. In Appendix A, we derive the following:

Proposition: Let $\mathbf{a}_i'$ be the i-th row of $\mathbf{A}$, $\phi(\mathbf{x};\boldsymbol{\mu},\boldsymbol{\Sigma})$ the multivariate normal density with mean $\boldsymbol{\mu}$ and variance $\boldsymbol{\Sigma}$ evaluated at $\mathbf{x}$, and $\gamma(x;\kappa,\tau)$ the gamma density with parameters κ and τ evaluated at x. If the likelihood and prior distributions of A, D, and B are as described in the main text, then for $\tilde{\mathbf{Y}}_i$ and $\tilde{\mathbf{X}}_i$ defined above, the posterior distribution can be written as:

$$p\left(\mathbf{A},\mathbf{D},\mathbf{B}\mid\mathbf{Y}_T\right) = p\left(\mathbf{A}\mid\mathbf{Y}_T\right)p\left(\mathbf{D}\mid\mathbf{A},\mathbf{Y}_T\right)p\left(\mathbf{B}\mid\mathbf{A},\mathbf{D},\mathbf{Y}_T\right)$$

with

$$p\left(\mathbf{D}\mid\mathbf{A},\mathbf{Y}_T\right) = \prod_{i=1}^{n}\gamma\left(d_{ii}^{-1};\kappa_i^*,\tau_i^*\right)$$

and

$$p\left(\mathbf{B}\mid\mathbf{A},\mathbf{D},\mathbf{Y}_T\right) = \prod_{i=1}^{n}\phi\left(\mathbf{b}_i;\mathbf{m}_i^*,d_{ii}\mathbf{M}_i^*\right),$$

where:

$$\begin{aligned}
\mathbf{m}_i^* &= \left(\tilde{\mathbf{X}}_i'\tilde{\mathbf{X}}_i\right)^{-1}\left(\tilde{\mathbf{X}}_i'\tilde{\mathbf{Y}}_i\right),\\
\mathbf{M}_i^* &= \left(\tilde{\mathbf{X}}_i'\tilde{\mathbf{X}}_i\right)^{-1},\\
\kappa_i^* &= \kappa_i + (T/2),\\
\tau_i^* &= \tau_i + \left(\zeta_i^*/2\right),\\
\zeta_i^* &= \left(\tilde{\mathbf{Y}}_i'\tilde{\mathbf{Y}}_i\right) - \left(\tilde{\mathbf{Y}}_i'\tilde{\mathbf{X}}_i\right)\left(\tilde{\mathbf{X}}_i'\tilde{\mathbf{X}}_i\right)^{-1}\left(\tilde{\mathbf{X}}_i'\tilde{\mathbf{Y}}_i\right),\\
p\left(\mathbf{A}\mid\mathbf{Y}_T\right) &= \frac{k_T p(\mathbf{A})\left[\det\left(\mathbf{A}\hat{\boldsymbol{\Omega}}_T\mathbf{A}'\right)\right]^{T/2}}{\prod_{i=1}^{n}\left[\left(2\tau_i^*/T\right)\right]^{\kappa_i^*}}\prod_{i=1}^{n}\left\{\frac{\left|\mathbf{M}_i^*\right|^{1/2}}{\left|\mathbf{M}_i\right|^{1/2}}\frac{\tau_i^{\kappa_i}}{\Gamma\left(\kappa_i\right)}\Gamma\left(\kappa_i^*\right)\right\},
\end{aligned}$$

where $\hat{\boldsymbol{\Omega}}_T$ is the covariance matrix of the reduced-form model and k_T is the constant ensuring that the density $p\left(\mathbf{A}\mid\mathbf{Y}_T\right)$ integrates to unity.

G Literature on the Pass-Through Effect in Costa Rica

This section analyzes previous estimates of the pass-through effect in Costa Rica, several of which are summarized in Table 3. Previous studies have applied various methodologies, covering different periods and considering specific characteristics detailed below.

A note on the comparability of estimates. Before delving into the analysis of previous estimates of the pass-through effect in Costa Rica, it is necessary to point out that some of them are not directly comparable due to differences in the transformation of the variables used and the data aggregation horizon.

To facilitate the comparison of the pass-through effect across different studies and samples, it is essential that all measures be expressed in terms of elasticities. However, the usual calculation of the pass-through effect is based on the relationship between the accumulated response of the price variable to a shock in the nominal exchange rate and the accumulated response of the nominal exchange rate to that shock. This calculation can be interpreted as an elasticity only if the logarithms[11] of the price level and exchange rate have been used in the specifications, or if the appropriate adjustment has been made to convert the coefficients into elasticities.

Even if an elasticity is obtained, it may represent different perspectives. For example, the elasticity of the price level to variations in the nominal exchange rate differs from the elasticity of inflation. The lack of methodological uniformity can introduce biases in conclusions and make it difficult to interpret results in different contexts.

In the specific case of the estimates mentioned in this section, all express price and exchange rate variables in percentage changes or their equivalent; however, they do so with different horizons (monthly, semi-annual, or annual).

Single-equation linear models. The first studies on the exchange rate pass-through effect in Costa Rica focused on the analysis of a symmetric effect using single-equation linear models estimated by Ordinary Least Squares (OLS). These studies were conducted mainly during the period when the crawling peg exchange rate regime was in place (León et al., 2001, 2002; Calderón Moya, 2005; Castrillo and Laverde, 2008; Rodríguez-Vargas, 2009). The results of these works suggest that the pass-through effect on overall inflation ranges between 5% and 16% in the short term (see Figure 12) and between 36% and 66% in the long term (see Figure 13).

One of the first studies estimates an inflation model for the period 1990-2001 (León et al., 2001), in which inflation is explained by variables such as nominal exchange rate depreciation, real exchange rate deviation, output gap, lagged inflation, and trade openness. A limitation of these single-equation approaches is that they ignore bidirectional relationships between variables, such as the interaction between exchange rate depreciation and inflation. It would be expected that exchange rate

[11] It is also possible to express the variables in first differences of the logarithm, which approximates percentage changes. In either case, impulse-response functions must be accumulated to express them in terms of elasticities.

variations are also affected by inflation since higher domestic inflation tends to depreciate the local currency. This bidirectional relationship is particularly relevant in a crawling peg regime, where exchange rate depreciations were guided by the difference between domestic and international inflation rates (Delgado, 2000).

Additionally, the model by León et al. (2001) omits monetary policy variables, such as interest rates or monetary aggregates[12]. The absence of these variables could generate endogeneity since monetary factors can simultaneously affect prices and the exchange rate, without price adjustments necessarily occurring through exchange rate variations. This issue has been highlighted by Shambaugh (2008b).

Subsequent studies (Calderón Moya, 2005; Castrillo and Laverde, 2008; Rodríguez-Vargas, 2009) have validated the model of León et al. (2001), obtaining similar results in the short term and some variations in the long term. In particular, Calderón Moya (2005) finds a long-term pass-through effect of 66%, while Castrillo and Laverde (2008) reports lower estimates, with a 6% effect in the short term and 33% in the long term.

Linear equation system models. Another group of studies (Calderón Moya, 2005; Esquivel Monge and Gomez Rodriguez, 2010; Orane, 2016; BCCR, 2023; Brenes-Soto et al., 2023) has analyzed the pass-through effect using linear equation system models, such as Vector Autoregressions (VAR) and Seemingly Unrelated Regressions (SUR).

VAR models are particularly useful when endogenous variables exist, meaning variables that influence each other. In these models, each endogenous variable is explained by its own lags and those of the other variables in the system, capturing complex dynamics.

Most previous studies employ recursive Cholesky identification, which allows for an orthogonal decomposition of shocks. However, this methodology has limitations, as it imposes restrictions on variable relationships that may be difficult to justify, and the variable ordering can significantly influence results (Shambaugh, 2008b).

In this context, Orane (2016) estimates a VAR with recursive identification for the period 2000-2014, including variables such as the exchange rate, the Monthly Economic Activity Index (IMAE), the Monetary Policy Rate (TPM), and a price index. Their results indicate a cumulative effect of 21.9% at one year and 34.3% in the long term. An update of these estimates, reported in BCCR (2023), finds that the general pass-through effect decreased to 12.3% during the flexible exchange rate period (2006-2022).

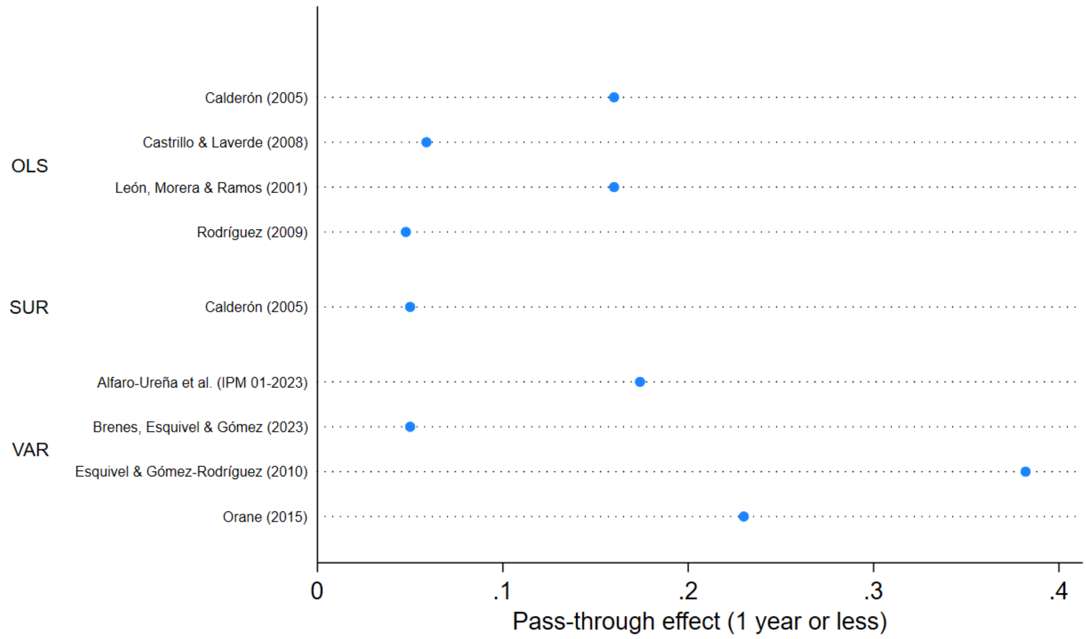
Nonlinear models. Recent studies (Esquivel Monge and Gomez Rodriguez, 2010; Brenes-Soto and Esquivel-Monge, 2018; Brenes-Soto et al., 2023) have explored nonlinear models to estimate the pass-through effect. Esquivel Monge and Gomez Rodriguez (2010) apply an LSTVAR model, finding evidence of asymmetries related to oil price variations. Likewise, Brenes-Soto and Esquivel-Monge (2018) find that the pass-through effect is greater in depreciations than in appreciations when shocks are of medium or large magnitude.

Finally, Brenes-Soto et al. (2023) estimate a VAR with endogenous regime switching, differentiating between high and low exchange rate shocks. Their results suggest

[12]It should be noted that during that period and until 2006, under a fixed exchange rate regime and free capital mobility, monetary policy had limited room for action.

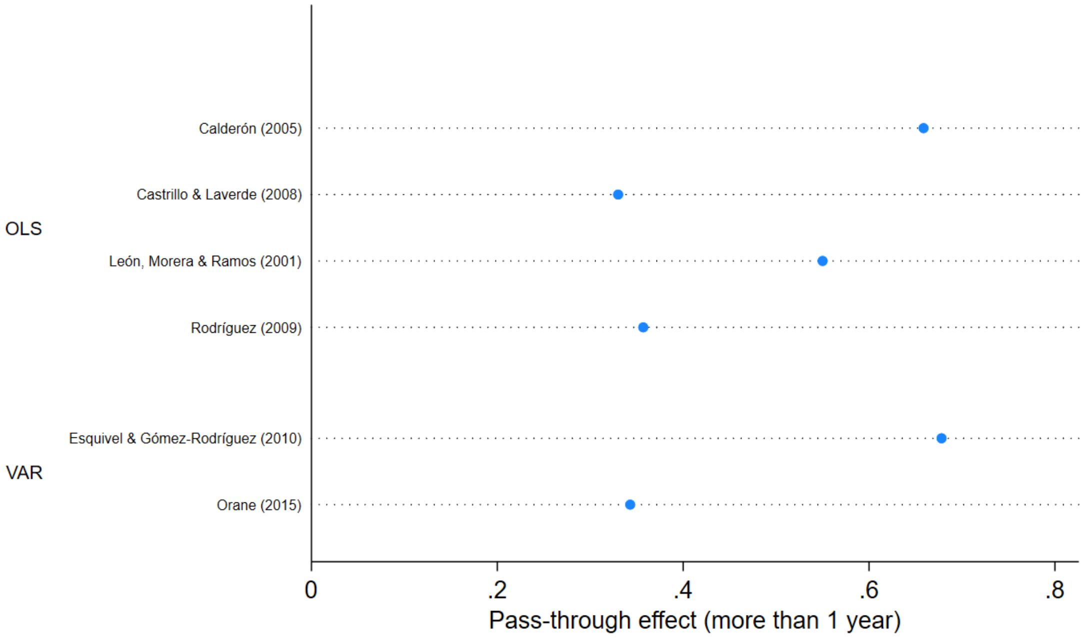
that the pass-through effect may be underestimated if the factors inducing exchange rate shocks are not considered.

Figure 12: Previous Estimates of the Short-Term Pass-Through Effect by Model and Author



Note: The values are not directly comparable due to the use of different time horizons in measuring the pass-through effect.

Figure 13: Previous Estimates of the Long-Term Pass-Through Effect by Model and Author



Note: The values are not directly comparable due to the use of different time horizons in measuring the pass-through effect.

Table 3: Previous Estimates of Exchange Rate Pass-Through in Costa Rica

N	Author	Period	Methodology	Breakdowns	Short-Term Pass-Through	Long-Term Pass-Through
1	León, Morera and Ramos (2001)	1991-2001	OLS	CPI	0,16	0,55
2	León, Laverde and Durán (2002)	1991-2001	OLS	Tradable	0,13	0,68
2	León, Laverde and Durán (2002)	1991-2001	OLS	Non-transable	0,10	0,52
3	Calderón Moya (2005)	1991-2003	OLS	CPI	0,16	0,66
3	Calderón Moya (2005)	1991-2003	OLS	Core Price Index	0,23	0,74
3	Calderón Moya (2005)	1991-2003	SUR	CPI	0,05	-
3	Calderón Moya (2005)	1991-2003	SUR	Core Price Index	0,10	-
4	Castrillo and Laverde (2008)	1991-2007	OLS	CPI	0,06	0,33
5	Rodríguez (2009)	1991-2009	MCO	CPI	0,05	0,36
6	Esquivel and Gómez-Rodríguez (2010)	1991-2009	LSTVAR	High regimen	0,24	0,47
6	Esquivel and Gómez-Rodríguez (2010)	1991-2009	LSTVAR	Low regimen	0,18	0,25
6	Esquivel and Gómez-Rodríguez (2010)	1991-2009	VAR	CPI	0,28	0,68
7	Orane (2015)	2000-2014	VAR	CPI	0,22	0,34
7	Orane (2015)	2006-2014	VAR	CPI	0,24	-
8	Brenes and Esquivel (2017)	2006-2017	SADLM	Small depreciation	-	0,22
8	Brenes and Esquivel (2017)	2006-2017	SADLM	Large depreciation	-	0,35
8	Brenes and Esquivel (2017)	2006-2017	SADLM	Small apreciation	-	0,00
8	Brenes and Esquivel (2017)	2006-2017	SADLM	Large apreciation	-	0,15
9	Brenes, Esquivel and Gómez (2023)	2009-2021	RS-VAR	High regimen	0,60	-
9	Brenes, Esquivel and Gómez (2023)	2009-2021	RS-VAR	Low regimen	0,05	-
9	Brenes, Esquivel and Gómez (2023)	2009-2021	VAR	CPI	0,05	-
10	Alfaro-Ureña et al. (IPM 01-2023)	2006-2015	VAR	CPI	0,29	-
10	Alfaro-Ureña et al. (IPM 01-2023)	2015-2022	VAR	CPI	0,11	-
10	Alfaro-Ureña et al. (IPM 01-2023)	2015-2022	VAR	CPI	0,12	-
11	Gómez-Rodríguez (2024)	2020-2023	SVAR	Undonditional	0,12	-

Note: SADLM: Structural Autoregressive Distributed Lag Model. RS-VAR: endogenous regime-switching vector autoregression.