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# Inflation Dynamics in a Small Open Economy: An SVAR Approach

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Fotografía de portada: “Presentes”, conjunto escultórico en bronce, año 1983, del artista costarricense Fernando Calvo Sánchez. Colección del Banco Central de Costa Rica.

# Dinámicas de inflación en una economía abierta y pequeña: Un enfoque SVAR

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## Resumen

Este artículo propone un modelo estructural de vectores autorregresivos (SVAR) para estudiar las fuerzas que impulsan la inflación en Costa Rica, una economía pequeña y abierta. Estimamos el modelo mediante métodos bayesianos y combinamos varias estrategias de identificación. La descomposición histórica resultante atribuye la dinámica de la inflación a distintos determinantes estructurales, incluidos choques de oferta, demanda, tipo de cambio y política monetaria, clasificados según su origen global o doméstico. La descomposición histórica atribuye el aumento de la inflación entre el cuarto trimestre de 2021 y el primer trimestre de 2023 principalmente a factores globales. La posterior desinflación, entre el segundo trimestre de 2023 y el primer trimestre de 2024, reflejó tanto una disminución de las presiones inflacionarias globales como una presión adicional a la baja proveniente de factores domésticos. Los choques domésticos de política monetaria contribuyeron poco a la inflación observada, con un promedio de alrededor de +0,07 puntos porcentuales por trimestre. Las expectativas de largo plazo se mantuvieron considerablemente más estables que la inflación general, mientras que la meta de inflación implícita en el modelo mostró una tendencia gradual a la baja y el choque asociado a esta contribuyó a la desinflación inicial. En conjunto, estos resultados muestran una relativa resiliencia, aunque no una alineación perfecta, del ancla nominal percibida y destacan la meta de inflación implícita como un indicador útil para evaluar el régimen de metas de inflación de Costa Rica.

**Palabras clave**: política monetaria; metas de inflación; meta implícita; anclaje de expectativas; economía pequeña y abierta; SVAR bayesiano; restricciones de signo; exogeneidad por bloques; descomposición histórica; Costa Rica.

**Clasificación JEL**.: E31, E52, F41, C32.

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The ideas expressed in this paper are those of the authors and not necessarily represent the view of the Central Bank of Costa Rica.

## Abstract

This article proposes a structural vector autoregression (SVAR) to study the forces driving inflation in Costa Rica, a small open economy. We estimate the model using Bayesian methods and combine several identification strategies. The resulting historical decomposition attributes inflation dynamics to structural drivers, including supply, demand, exchange-rate, and monetary-policy shocks, classified according to their global or domestic origin. The historical decomposition attributes the inflation surge from 2021Q4 to 2023Q1 primarily to global factors. The subsequent disinflation from 2023Q2 to 2024Q1 reflected both a decline in global inflationary pressures and additional downward pressure from domestic factors. Domestic monetary-policy shocks contributed little to realized inflation, averaging about +0.07 percentage points per quarter. Long-run expectations remained considerably more stable than headline inflation, while the model-implied inflation target displayed a gradual downward drift and its associated shock contributed to the initial disinflation. Taken together, these results identify relative resilience, but not perfect alignment, of the perceived nominal anchor and highlight the implicit inflation target as a useful indicator for evaluating Costa Rica's inflation-targeting regime.

**Key words:** monetary policy; inflation targeting; implicit target; expectations anchoring; small open economy; Bayesian SVAR; sign restrictions; block exogeneity; historical decomposition; Costa Rica.

**JEL codes**: E31, E52, F41, C32.

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# 1 Introduction

The global inflation surge of 2022 brought renewed urgency to understanding the forces driving inflation. A growing literature has studied the post-pandemic episode by separating the contributions of demand and supply disturbances (Bergholt et al., 2024, 2026; Firat and Hao, 2023; Kabaca and Tuzcuoglu, 2023, among others). Although their estimated importance varies across countries and over time, both types of disturbances are generally found to have contributed to the surge. Yet this broad distinction can obscure important differences in the origin and nature of inflationary pressures. Domestic demand disturbances, for example, need not have the same interpretation or policy implications as foreign demand or supply disturbances (Bergholt et al., 2026), while more granular decompositions distinguish among supply-chain, commodity-price, labor-market, and other shocks (Kabaca and Tuzcuoglu, 2023). The post-pandemic episode therefore poses a sharper identification question: which specific disturbances drove inflation, and did they originate domestically or abroad? Answering this question is particularly important for small open economies, where global and domestic inflationary pressures can require very different policy responses.

Costa Rica provides a particularly revealing setting in which to study these questions. After the Central Bank of Costa Rica (BCCR) consolidated an inflation-targeting framework centered on a 3% target with a $\pm 1$ percentage-point tolerance band, headline inflation remained persistently below the band during the pre-pandemic years, surged above 10% during the global inflation episode, and then fell sharply into negative territory in 2023, remaining unusually low through 2025.[1] Whereas post-2022 disinflation in the major Latin American inflation-targeting economies generally brought inflation back toward target while remaining positive, Costa Rica moved from a substantial overshoot to a substantial undershoot within roughly two years. This sharp reversal makes it particularly important to determine how much of the observed inflation dynamics reflected global shocks, domestic conditions, and monetary policy.

We address this question by estimating a ten-variable Bayesian SVAR for Costa Rica and its external environment over 2009Q1–2026Q2. Identification combines small-open-economy block exogeneity with sign restrictions imposed over specific horizons. Block exogeneity allows external variables to affect the domestic economy contemporaneously and dynamically, while ruling out feedback from domestic disturbances to global variables. Sign and horizon restrictions then distinguish shocks that timing assumptions alone cannot separate, including oil supply from oil demand, global supply from global demand, and domestic supply from domestic demand. The resulting decomposition identifies both the nature and origin of inflationary pressures, helping separate external forces largely beyond the central bank's control from domestic developments that monetary policy can influence more directly.

One contribution of the paper is to combine four complementary identification strategies, each resolving a different source of structural ambiguity. Block exogeneity separates global from domestic forces by preventing domestic variables from feeding back into a five-variable global block, either

[1] As part of its transition toward the current framework, the BCCR progressively lowered its inflation target from 8% in 2008 to 5% in 2009, 4% in 2014, and 3% in 2016.

contemporaneously or dynamically. Sign restrictions distinguish demand from supply disturbances at both levels, with additional post-impact restrictions sharpening the identification of oil shocks. Selected contemporaneous zero restrictions further separate shocks with otherwise similar implications, most notably by ruling out a within-quarter monetary-policy response to an autonomous exchange-rate shock. Finally, following Mumtaz and Theodoridis (2023), a maximum forecast-error-variance restriction identifies the implicit inflation-target shock as the domestic disturbance that explains the largest share of the long-horizon variance of long-run inflation expectations. The contribution lies in bringing these restrictions together within a coherent framework, allowing us to recover ten economically distinct shocks and trace both the nature and origin of Costa Rica's inflation dynamics.

Beyond decomposing inflation, the framework evaluates monetary policy along two distinct dimensions: unexpected policy actions and the behavior of the perceived nominal anchor. The identified monetary-policy shock captures policy surprises, while the *implicit inflation target*, inferred from long-run expectations, captures the inflation rate that economic agents perceive the BCCR to pursue over time. Comparing this implicit target with the BCCR's explicit target provides an indicator of the degree to which the perceived nominal anchor remained aligned with the announced objective. This distinction is especially informative when inflation is driven by external forces, since deviations of realized inflation from target need not, by themselves, signal a loss of monetary-policy credibility.

We report the historical decomposition through four internally consistent aggregations of the ten identified shocks, distinguishing global from domestic forces, supply from demand forces, supply and demand shocks by origin, and domestic monetary-policy and exchange-rate shocks from all other forces.

**Main findings.** Three main results emerge. First, global shocks dominate both the inflation surge and the later period of below-target inflation, while the initial reversal reflects both fading global pressures and additional domestic downward pressure. During 2021Q4–2023Q1, global shocks contributed about $+5.2\,p.p.$ per quarter to the deviation of inflation from its model-implied baseline, compared with approximately $-0.9\,p.p.$ from domestic shocks. In the transition to 2023Q2–2024Q1, the global contribution fell to near zero, while the domestic contribution became more negative, averaging about $-4.3\,p.p.$ per quarter. Thus, the decline in inflation reflected both forces, even though domestic shocks accounted for most of the negative inflation gap within the initial-disinflation window. From 2024Q2 to 2026Q2, global forces again became the main proximate driver of inflation below the tolerance band, contributing approximately $-2.3\,p.p.$ per quarter.

Second, domestic monetary-policy shocks contributed little to realized inflation, averaging about $+0.07\,p.p.$ per quarter over the inflation-targeting period and $+0.25\,p.p.$ during the surge. Policy surprises therefore appear not to have been a major direct driver of inflation dynamics.

Third, the implicit inflation target and observed long-run expectations remained considerably more stable than headline inflation, but their behavior points to different degrees of alignment.

Observed long-run expectations varied within a narrow range of 1.9% to 3.2%, while the implicit target ranged from 0.8% to 4.2% and drifted below the BCCR's tolerance band during part of the sample. The implicit-target shock also made a non-negligible disinflationary contribution, particularly during 2023Q2–2024Q1. These findings indicate that the perceived nominal anchor was substantially more resilient than realized inflation, although it was not perfectly aligned with the explicit target throughout the period.

**Relation to the literature and contribution.** Our paper contributes first to the literature on the drivers of post-pandemic inflation and inflation dynamics in small open economies. Recent studies find that both demand and supply disturbances contributed to the inflation surge, while emphasizing that their relative importance and economic origin vary across countries and over time (Bergholt et al., 2024, 2026; Firat and Hao, 2023; Kabaca and Tuzcuoglu, 2023). Related work shows that global disturbances can account for an important share of inflation and output fluctuations in small open economies (Corbo and Di Casola, 2022; Cushman and Zha, 1997; Finck and Tillmann, 2022). We bring these dimensions together in a structural decomposition that distinguishes global from domestic forces and demand from supply disturbances, while separately identifying oil, monetary-policy, exchange-rate, and implicit-target shocks. This decomposition helps separate external forces largely beyond the BCCR's control from domestic developments that monetary policy can influence more directly.

Second, we contribute to the literature that uses long-run inflation expectations to infer the central bank's perceived inflation objective. Following Mumtaz and Theodoridis (2023), we identify an implicit inflation-target shock using a max-FEV restriction, but embed it in a small-open-economy SVAR in which nine additional global and domestic shocks are identified simultaneously. Moreover, because the BCCR announces a numerical inflation target, the estimated implicit target can be directly compared with the explicit objective. This comparison provides a measure of the degree to which the perceived nominal anchor remained aligned with the announced target during a period of unusually large inflation fluctuations.

Finally, the paper contributes to the literature on inflation and monetary policy in Costa Rica. Previous studies have examined imported inflation (Durán-Víquez and Torres-Gutiérrez, 2007), oil-price transmission (Hoffmaister et al., 2000), the anchoring of inflation expectations (Muñoz-Salas and Torres-Gutiérrez, 2006; Segura-Rodríguez, 2019), international monetary-policy spillovers (Barquero-Romero and Chávez-López, 2018), and exchange-rate pass-through (Gómez-Rodríguez and Sandoval-Alvarado, 2025). We place these channels within a unified structural framework and estimate their contributions jointly. To our knowledge, this is the first structural historical decomposition of Costa Rican inflation that jointly distinguishes the nature and origin of inflationary disturbances while relating monetary-policy surprises to the behavior of the perceived nominal anchor.

**Roadmap.** Section 2 introduces the variables and explains how data observed at different frequencies are assembled into a quarterly sample. Sections 3.1 and 3.2 develop the empirical framework, moving from the reduced-form Bayesian VAR and its prior to the restrictions used to distinguish ten global and domestic structural shocks. Section 4 first uses impulse responses to establish the economic interpretation of these shocks and then employs historical decompositions to trace the forces driving Costa Rican inflation. The policy discussion in Section 4.8 brings these results together by relating the limited contribution of monetary-policy surprises and the behavior of the implicit target to the conduct of monetary policy. Sections 5.1 and 5.2 assess this interpretation using evidence from the BCCR's Monetary Policy Reports, model diagnostics, and alternative inflation and data-aggregation specifications. Section 6 summarizes the implications for the evaluation of inflation targeting in Costa Rica and discusses the main limitations of the analysis.

# 2 Data and variable construction

## 2.1 Variables

The model comprises ten endogenous variables, ordered so that the first five constitute an exogenous global block and the last five a domestic block. Table 1 lists them together with their construction and source. The global block collects the external conditions relevant for a small commodity-importing economy: international fuel prices, non-fuel commodity prices, a measure of U.S. real activity (the output gap), trading-partner inflation, and the U.S. monetary-policy stance (proxied over the zero-lower-bound years by the Wu–Xia shadow federal funds rate). The domestic block collects the nominal exchange rate, long-run (60-month) inflation expectations, headline consumer-price inflation, the Costa Rican output gap, and the BCCR monetary policy rate (*tasa de política monetaria*, TPM).

Table 1: Model variables, transformations, and sources

| Line | Code | Variable | Description | Source |
|---|---|---|---|---|
| | | **Panel A. Global block** | | |
| 1 | `pComb` | Fuel prices | International Raw-Materials Price Index–Fuels[a] | BCCR |
| 2 | `pMSC` | Non-fuel commodity prices | International Raw-Materials Price Index–Total excluding fuels[a] | BCCR |
| 3 | `gapUS` | U.S. output gap | Own analysis from real quarterly GDP (FRED: GDPC1)[b] | FRED |
| 4 | `infSC` | Trading-partner inflation | Trading-partner inflation index[c] | BCCR |
| 5 | `iUS` | U.S. monetary policy rate | U.S. effective federal funds rate (FRED: EFFR) or Wu-Xia shadow rate at the ZLB[d] | FRED and Wu-Xia |
| | | **Panel B. Domestic block** | | |
| 6 | `tcn` | Nominal exchange rate | Nominal exchange rate (CRC/USD)[e] | BCCR |
| 7 | `exp60` | Long-run inflation expectations | 60-month market inflation expectations | BCCR |
| 8 | `infCR` | Headline inflation | Year-on-year percentage change of the Consumer Price Index (CPI) | BCCR |
| 9 | `gapCR` | Costa Rican output gap | Own analysis from real quarterly GDP (2022 base year)[f] | BCCR |
| 10 | `tpm` | Monetary-policy rate | Monetary Policy Rate (TPM) | BCCR |

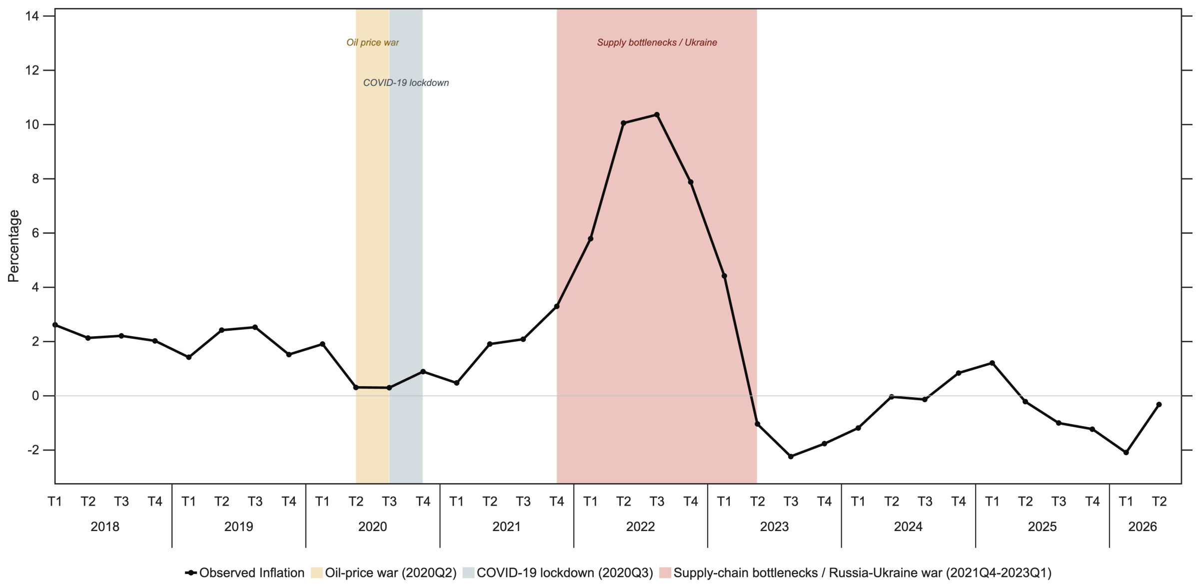
*Notes:* (a) An internal BCCR product, not published on the public indicators portal, covering the fuel and non-fuel components separately. (b) Built from the raw GDP series rather than an official U.S. output-gap estimate: published output-gap measures are typically released with a substantially longer lag than real GDP itself, so the gap is obtained in-house with an HP filter ($\lambda = 1600$) to keep the series current. (c) A weighted index of consumer-price inflation across Costa Rica's main trading partners, elaborated by the BCCR. (d) The effective federal funds rate is replaced, in months where the Wu–Xia shadow rate is negative (the zero-lower-bound period), by that shadow rate, so the series reflects the stance of unconventional U.S. monetary policy when the nominal rate was constrained at zero. (e) Average of the BCCR's daily buy and sell colón/US$ reference rates, aggregated to monthly and entered as a monthly percentage change; a log-level alternative is available in the underlying code. (f) Analogous to the U.S. gap: constructed in-house via an HP filter ($\lambda = 15{,}917$, the Costa Rica-calibrated monthly smoothing parameter of Gómez-Rodríguez (2023)) applied to BCCR's monthly real GDP series, since Costa Rica does not publish an official real-time output gap.

Figure 1 plots the response variable in the center of the document – the Costa Rican inflation target year-on-year (`infCR`) – exactly as it enters the model, during the inflation-targeting period. The shaded episodes mark where the identified structural shocks coincide with surprise events documented in the BCCR's own Monetary Policy Reports; this narrative cross-check is developed in full in Section 5.1.

## 2.2 Frequency, sample, and aggregation

Source series arrive at daily, monthly, and quarterly frequencies. They are aligned to a common *quarterly* frequency, which is the lowest frequency among the series entering the estimated model and therefore the frequency at which a common non-missing sample is available. When aggregating higher-frequency data to the model frequency, the baseline uses the last-value-in-period convention (end-of-quarter), with a within-period mean as a robustness alternative (Section 5.2.2). The estimation sample is the longest common non-missing span, 2009Q1-2026Q2, yielding $T = 70$ quarterly

Figure 1: Costa Rican headline inflation (`infCR`), 2018-2026.




**Notes:** Shaded bands mark episodes where the identified shocks coincide with surprise events documented in the BCCR's Monetary Policy Reports (IPM); see Section 5.1 for the full narrative cross-check.

observations after alignment and the removal of rows with missing values. Although the IT regime is the object of interest, we rely on the full sample to sharpen the estimation of the dynamics, and we narrow the historical decomposition on the IT period 2018-2026. This is a deliberate choice: restricting estimation to the post-2018 window would leave too few degrees of freedom for a ten-variable system, whereas the historical decomposition is a sample-path object that can be read over any subwindow of interest.

# 3 Empirical framework

## 3.1 The reduced-form Bayesian VAR

### 3.1.1 Specification

Let $y_t$ be the $n \times 1$ vector of endogenous variables ($n = 10$), ordered as in Table 1. The reduced-form VAR is

$$y_t = c + \sum_{\ell=1}^{p} B_\ell \, y_{t-\ell} + u_t, \qquad u_t \sim \mathcal{N}(0, \Sigma), \tag{1}$$

with $p = 2$ lags selected by the Bayesian information criterion, an intercept $c$, and reduced-form innovations $u_t$ with covariance $\Sigma$. Stacking observations we can write (1) as $Y = X\beta + U$, where the rows of $X$ collect the intercept and $p$ lagged variables.

### 3.1.2 Prior

We use a Minnesota-type Normal-inverse-Wishart prior with several refinements standard in the modern BVAR literature (Bańbura et al., 2010; Litterman, 1986; Sims and Zha, 1998). The implementation is as follows. The prior mean shrinks own first lags toward a coefficient of $\phi_{\text{own}} = 0.30$ (rather than the random-walk value of one, appropriate for approximately stationary transformations such as inflation, gaps, and rate changes) and all other coefficients toward zero. The prior variances are governed by an overall tightness $\lambda_1 = 0.10$, a cross-variable tightness $\lambda_2 = 3.5$ (relatively loose, allowing rich cross-variable dynamics), a lag-decay parameter $\lambda_3 = 3$ (higher lags shrunk more aggressively), and a loose prior on the intercept (tightness 10). The innovation covariance carries an inverse-Wishart prior with $\nu = 11$ degrees of freedom and a unit scale. We additionally impose a *single-unit-root* ("dummy initial observation" or co-persistence) prior, originally proposed by Sims (1993), with a small hyperparameter $\delta = 10^{-4}$ and a sample-based mean. This prior disciplines the deterministic component and the low-frequency behavior of the VAR, which is particularly important in our application because uncertainty in the deterministic component can translate into substantial instability in historical shock decompositions; a sufficiently tight single-unit-root prior sharply reduces this source of uncertainty across posterior draws Bergholt et al. (2024). The sum-of-coefficients prior is switched off in the baseline.

Explicitly, writing $B_{ij\ell}$ for the coefficient on variable $j$ at lag $\ell$ in equation $i$ and $c_i$ for the intercept of equation $i$, the prior variances are

$$\text{Var}(B_{ij\ell}) = \frac{\lambda_1^2}{\ell^{2\lambda_3}} \frac{\sigma_i^2}{\sigma_j^2} \begin{cases} 1, & j = i \\ \lambda_2^2, & j \neq i \end{cases}, \qquad \text{Var}(c_i) = (\lambda_1 \lambda_c)^2 \, \sigma_i^2, \tag{2}$$

with intercept tightness $\lambda_c = 10$ and $\sigma_i^2$ the residual variance from a univariate AR(1) fit to series $i$, used only to rescale the prior for differences in variable units—a standard Minnesota-prior device, not a data-dependent empirical-Bayes step. The prior mean is 0 for every coefficient except the own-first-lag coefficients, which are centered at $\phi_{\text{own}}$ as described above.

The hyperparameters are chosen with the model's purpose in mind rather than by a formal search. Because the object of interest is the transmission of global shocks into the domestic block, the cross-variable tightness $\lambda_2 = 3.5$ is set *loose*—well above the own-variable benchmark of 1—so the prior does not fight the very spillovers the model is built to capture; a conventional Minnesota calibration, which shrinks cross-equation coefficients toward zero far more aggressively than $\lambda_2 > 1$ would, is appropriate for pure forecasting but would understate exactly the transmission channels studied here. The lag-decay parameter $\lambda_3 = 3$ compensates by shrinking the second lag much more tightly than the first ($\ell^{-2\lambda_3} \approx 0.016$ at $\ell = 2$, versus 1 at $\ell = 1$), which keeps the ten-variable, two-lag system ($k = 1 + 10 \times 2 = 21$ regressors per equation) from overfitting the $T = 68$ post-lag observations despite the loose cross-variable setting. The overall tightness $\lambda_1 = 0.10$ and the loose intercept prior ($\lambda_c = 10$) are conventional default magnitudes for Minnesota-type BVARs of this size, and the inverse-Wishart scale $S_0 = \text{diag}(\sigma_1^2, \ldots, \sigma_{10}^2)$ centers the covariance prior on the same

AR(1)-implied variances used to scale the coefficient prior, with $\nu = 11$ degrees of freedom left only marginally above the number of variables so that the sample, not the prior, dominates the estimation of $\Sigma$.

#### 3.1.3 Block exogeneity in the prior

The global block (variables 1–5) is treated as block-exogenous with respect to the domestic block (variables 6–10). Operationally, the prior standard deviation on every coefficient through which a *domestic* lag would enter a *global* equation is set to a near-zero value ($10^{-4}$), so that the posterior is tightly concentrated at zero for those coefficients. This encodes the small-open-economy restriction that Costa Rican developments do not feed back onto world commodity prices, U.S. activity, partner inflation, or U.S. policy—at any lag. Block exogeneity is imposed *dynamically* here (on lagged coefficients); the contemporaneous counterpart is handled at the identification stage in Section 3.2.

#### 3.1.4 Posterior sampling and stability

We draw from the posterior with a Gibbs sampler: 100,000 draws after a burn-in of 10,000, retaining only draws that deliver a stable companion matrix. In the baseline run, 49,678 of 50,000 post-burn attempts are stable (a stability rate of 99.4%), with a median spectral radius of 0.90 and a 90th percentile of 0.95, comfortably inside the unit circle and consistent with the mean-reverting behavior expected of the transformed series. These reduced-form draws are the input to the structural identification.

### 3.2 Structural identification

We map reduced-form innovations $u_t$ to $n$ structural shocks $\varepsilon_t$ through an impact matrix $A_0^{-1}$, with $u_t = A_0^{-1}\varepsilon_t$ and $\mathbb{E}[\varepsilon_t \varepsilon_t'] = I_n$. Any such $A_0^{-1}$ can be written $A_0^{-1} = L\,Q$, where $L$ is the lower-triangular Cholesky factor of $\Sigma$ and $Q$ is orthogonal. Identification amounts to selecting the columns of $Q$ so that the implied impact and dynamic responses satisfy the restrictions below. We follow the rejection-sampling logic of Rubio-Ramírez et al. (2010) and Arias et al. (2018), combining it with the block structure and a max-FEV step.

#### 3.2.1 Contemporaneous block exogeneity and the domestic shock space

Dynamic block exogeneity (Section 3.1.3) is complemented by a contemporaneous restriction: domestic structural shocks must not move the global block on impact *or* at the horizons over which restrictions are evaluated. Concretely, we form the matrix of stacked global responses to candidate shocks and take its null space; *domestic* shocks are restricted to lie in that null space (a five-dimensional subspace, given five domestic variables). This guarantees that the five domestic shocks (exchange-rate, implicit-target, domestic-supply, domestic-demand, and domestic-monetary-policy) leave fuel prices, non-fuel commodity prices, partner inflation, U.S. activity, and the U.S. rate unaffected. These are the contemporaneous analogue of the small-open-economy assumption. The five global shocks are then identified within the complementary space.

#### 3.2.2 Domestic shocks

Within the domestic subspace defined by the block-exogeneity restriction, we identify five shocks: an implicit inflation-target shock, a monetary-policy shock, a nominal exchange-rate shock, an aggregate-demand shock, and an aggregate-supply shock. By construction, these disturbances do not affect the variables in the global block, either contemporaneously or dynamically. This restriction follows the standard small-open-economy assumption that domestic developments do not feed back into external prices, activity, inflation, or monetary policy (Cushman and Zha, 1997; Hoffmaister et al., 2000).

An **implicit inflation-target shock** is defined as an unexpected change in the economy's perceived long-run nominal anchor. Following Mumtaz and Theodoridis (2023), we identify it as the domestic structural innovation that maximizes the contribution to the forecast-error variance of 60-month inflation expectations accumulated over 24 quarters. The identifying assumption is that conventional demand, supply, and monetary-policy shocks may affect long-horizon expectations temporarily, but their effects should dissipate at longer horizons if the monetary authority is perceived to be credible. Persistent innovations in long-run expectations can therefore be associated with changes in the perceived inflation target. The maximum-variance approach follows Uhlig (2004) and Barsky and Sims (2011). No sign restrictions are imposed on the responses of the other domestic variables.

A **domestic monetary-policy shock** is defined as an unexpected increase in the BCCR's monetary-policy rate. A contractionary shock is identified by imposing an increase in the policy rate and contemporaneous declines in inflation and the output gap, together with an appreciation of the domestic currency. These restrictions capture the conventional monetary-transmission mechanism in a small open economy: a policy tightening weakens aggregate demand and inflation while higher domestic interest rates tend to appreciate the currency. Cushman and Zha (1997) document this pattern for a small open economy, while Barquero-Romero and Chávez-López (2018) obtain a similar transmission mechanism for Costa Rica. Related sign-restricted SVAR applications identify contractionary monetary shocks through higher policy rates and lower inflation and activity (Finck and Tillmann, 2022; Peersman, 2005). The response of long-run inflation expectations is left unrestricted.

A **nominal exchange-rate shock** is defined as an unexpected depreciation of the Costa Rican colón that is not itself generated by a contemporaneous monetary-policy innovation. It is identified by imposing an increase in the nominal exchange rate and domestic inflation on impact, together with a zero contemporaneous response of the BCCR policy rate. The positive inflation response captures exchange-rate pass-through, while the exclusion restriction distinguishes an autonomous exchange-rate disturbance from a monetary-policy shock within the same quarter. Ganiko and Jiménez (2023) employ a similar contemporaneous exclusion restriction in identifying exchange-rate disturbances. More generally, Forbes et al. (2018) emphasize that the inflationary consequences of exchange-rate movements depend on the structural shock causing the currency to move, providing a rationale for identifying exchange-rate shocks separately rather than treating observed exchange-rate innovations as exogenous. The responses of the output gap and long-run inflation expectations are left unrestricted.

A **domestic aggregate-demand shock** is defined as an unexpected expansion in domestic demand. It is identified by imposing contemporaneous increases in both inflation and the output gap, while the responses of the remaining domestic variables are left unrestricted. The restriction exploits the standard prediction that demand disturbances move prices and economic activity in the same direction. This identifying principle is widely used in sign-restricted VARs (Finck and Tillmann, 2022; Peersman, 2005) and is also the basis for the demand-supply decomposition of Firat and Hao (2023), who classify disturbances as demand-driven when prices and quantities move in the same direction.

A **domestic aggregate-supply shock** is defined as an unexpected adverse supply disturbance that raises inflation while reducing domestic economic activity. Accordingly, it is identified by imposing a contemporaneous increase in inflation and a decline in the output gap. This stagflationary comovement distinguishes supply disturbances from demand shocks and is consistent with the identification strategies of Peersman (2005), Finck and Tillmann (2022), and Firat and Hao (2023). The remaining domestic responses are unrestricted and determined by the model.

### 3.2.3 Global shocks

Within the complementary global subspace, we identify five shocks: a U.S. monetary-policy shock, an oil-supply shock, an oil-demand shock, a global aggregate-demand shock, and a global aggregate-supply shock. Unlike domestic disturbances, global shocks may affect both the external and Costa Rican variables. The sign restrictions distinguish shocks with different economic origins even when they generate similar movements in individual global variables.

A **U.S. monetary-policy shock** is defined as an unexpected tightening in the U.S. monetary-policy stance. It is identified by imposing an increase in the U.S. policy rate together with contemporaneous declines in U.S. economic activity and trading-partner inflation. These restrictions distinguish a contractionary monetary-policy innovation from endogenous increases in the policy rate associated with stronger activity or inflation. The international transmission of U.S. monetary shocks to emerging and small open economies is documented by Canova (2005) and Mackowiak (2007). For Costa Rica, Barquero-Romero and Chávez-López (2018) show that an unexpected increase in international interest rates induces capital outflows, currency depreciation, and weaker domestic activity. The responses of the remaining variables are left unrestricted.

An **oil-supply shock** is defined as an unexpected adverse disturbance to global oil-supply conditions that raises international fuel prices and weakens economic activity. We therefore impose an increase in fuel prices and a decline in U.S. activity on impact, together with a zero contemporaneous response of non-fuel commodity prices, which separates a fuel-specific supply disturbance from the broad-based oil-demand shock below that lifts non-fuel commodity prices as well. Costa Rican inflation is restricted to increase at the first post-impact horizon, rather than contemporaneously, reflecting the regulated delay with which international fuel-price movements are transmitted to domestic prices. The distinction between supply- and demand-driven oil-price movements follows Kilian (2009), who emphasizes that the macroeconomic consequences of an oil-price increase depend on its structural origin. Independent evidence from Känzig (2021), based on high-frequency identification around OPEC announcements, shows that adverse oil-supply news raises oil prices while reducing economic activity and increasing prices and inflation expectations. The delayed restriction for Costa Rican inflation is also consistent with Hoffmaister et al. (2000), who document a lagged transmission from international oil prices to domestic inflation.

An **oil-demand shock** is defined as an unexpected demand-driven increase in fuel prices associated with stronger global economic activity. It is identified by contemporaneous increases in fuel prices, non-fuel commodity prices, and U.S. activity, together with an increase in Costa Rican inflation at the first post-impact horizon. This shock is therefore closest to what the oil-market literature describes as an oil-demand shock driven by global economic activity, rather than an oil-market-specific precautionary-demand shock (Kilian, 2009; Peersman and Van Robays, 2012). Its defining feature in our system is the contemporaneous commodity-price response, particularly the required increase in fuel prices. The delayed restriction on Costa Rican inflation reflects the institutional lag in the transmission of international fuel prices documented by Hoffmaister et al. (2000). The remaining responses, including trading-partner inflation, are unrestricted.

A **global aggregate-demand shock** captures a broader expansion in world demand. It is identified by contemporaneous increases in U.S. activity, trading-partner inflation, non-fuel commodity prices, and Costa Rican inflation, while the response of fuel prices is left unrestricted. Thus, unlike the oil-demand shock, its identification does not require a movement in fuel prices; instead, it requires the broader activity-inflation comovement characteristic of an aggregate-demand disturbance. This distinction is similar in spirit to empirical frameworks that separate broad global demand disturbances from oil or commodity-price shocks (Charnavoki and Dolado, 2014; Finck and Tillmann, 2022; Ha et al., 2023). Because a sufficiently strong global demand expansion may nevertheless also raise fuel prices, the two shocks can generate similar observable responses. We therefore avoid placing substantive weight on their individual contributions and emphasize the aggregated global-demand contribution in the historical decomposition below.

Finally, a **global aggregate-supply shock** is defined as an unexpected adverse global cost-push disturbance that increases inflationary pressures while depressing economic activity. It is identified by imposing a contemporaneous increase in trading-partner inflation and Costa Rican inflation together with a decline in the U.S. output gap. This opposite movement of inflation and activity is the standard empirical signature of an adverse supply shock and mirrors the identifying logic used for domestic supply disturbances (Finck and Tillmann, 2022; Firat and Hao, 2023; Peersman, 2005). The responses of commodity prices, the U.S. policy rate, and the remaining Costa Rican variables are unrestricted and determined by the model.

An important distinction must be made regarding between (demand and supply) oil shocks and broader (demand and supply) global shocks. Identification of the two sets separates shocks according to their primary contemporaneous effect in the global block. Oil shocks are disturbances whose defining response is concentrated in fuel prices, whereas the broader global shocks are identified from the joint behavior of global activity and trading-partner inflation. This distinction follows two related strands of the literature. The oil-market literature emphasizes that increases in oil prices can originate from oil supply disturbances, from stronger global economic activity, or from demand disturbances specific to the oil market (Kilian, 2009; Peersman and Van Robays, 2012). A separate literature on inflation in open economies distinguishes broad global demand and supply disturbances from commodity- or oil-price shocks (Charnavoki and Dolado, 2014; Ha et al., 2023). Our specification combines these two perspectives within the same global block. Consequently, the individual oil and global demand shocks should be interpreted as a fine decomposition of global demand pressures rather than as entirely independent economic forces. The broader results below therefore also report aggregations that combine shocks by demand/supply type and region.

Table 2 summarizes the identifying restrictions. Sign restrictions are imposed on impact except where noted; oil shocks additionally use the first post-impact ($h = 1$) response of domestic inflation; the exchange-rate shock uses a contemporaneous zero restriction on the policy rate; and the implicit-target shock uses a max-FEV criterion rather than a sign.

Table 2: Identifying restrictions

| Shock ↓ / Response → | Type | Global block | | | | | Domestic block | | | | |
|---|---|---|---|---|---|---|---|---|---|---|---|
| | | `pComb` (1) | `pMSC` (2) | `gapUS` (3) | `infSC` (4) | `iUS` (5) | `tcn` (6) | `exp60` (7) | `infCR` (8) | `gapCR` (9) | `tpm` (10) |
| A. Global shocks | | | | | | | | | | | |
| Oil supply | S | + | | − | | | | | $+^{h1}$ | | |
| Global supply | S | | | − | + | | | | + | | |
| Oil demand | D | + | + | + | | | | | $+^{h1}$ | | |
| Global demand | D | | + | + | + | | | | + | | |
| U.S. monetary policy | D | | | − | − | + | | | | | |
| B. Domestic shocks | | | | | | | | | | | |
| Exchange rate | S | ● | ● | ● | ● | ● | + | | + | | 0 |
| Implicit target | S | ● | ● | ● | ● | ● | | FEV | | | |
| Domestic supply | S | ● | ● | ● | ● | ● | | | + | − | |
| Domestic demand | D | ● | ● | ● | ● | ● | | | + | + | |
| Monetary policy | D | ● | ● | ● | ● | ● | − | | − | − | + |

*Notes:* + and − denote the sign of the response, while 0 denotes a contemporaneous exclusion restriction. The superscript $h1$ indicates that the sign restriction is imposed at the first post-impact horizon, and FEV denotes the forecast-error-variance maximization criterion. The symbol ● indicates that, for domestic shocks, responses of variables in the global block are restricted to zero over the full restriction-evaluation horizon ($h = 0$–$3$; Section 3.2); blank cells are unrestricted. The "Type" column classifies shocks as demand (D) or supply-type (S) according to the co-movement restrictions used for identification (Section 3.2). Variable abbreviations are as follows: `pComb`, fuel prices; `pMSC`, non-fuel commodity prices; `gapUS`, U.S. output gap; `infSC`, trading-partner inflation; `iUS`, U.S. policy rate; `tcn`, nominal exchange rate; `exp60`, long-run inflation expectations; `infCR`, headline inflation; `gapCR`, Costa Rican output gap; and `tpm`, Costa Rican monetary-policy rate. For more information see Table 1.

#### 3.2.4 Sampling the structural model

Within each block, shocks are identified *sequentially*: once a shock's direction is fixed, every subsequent shock in the same block is drawn from the orthogonal complement of all previously fixed directions (intersected with the domestic or global subspace, as appropriate), so the admissible space shrinks by one dimension each time a shock is pinned down—the standard construction underlying the rejection-sampling algorithms of Arias et al. (2018); Rubio-Ramírez et al. (2010). The implicit-target shock is the only *deterministic* direction at the point it is identified—the leading eigenvector of the accumulated squared-response matrix in the max-FEV criterion—so it is identical across every candidate rotation for a given reduced-form draw. The monetary-policy, exchange-rate, domestic-demand, U.S.-monetary-policy, oil-supply, and oil-demand shocks are each drawn as a uniformly random unit vector within their (shrinking) admissible subspace and re-drawn, independently of the other shocks, up to 100 times if the sign (or zero, or first-post-impact) restriction fails; the domestic-supply and global-supply shocks are not drawn at all but are the sole remaining direction in their subspace once every other shock in the block is fixed, so only their *sign* is checked. A "candidate" in the count below is one full pass through this sequence for both blocks; if any shock's 100 inner draws are exhausted, or a residual direction fails its sign check, the entire candidate is discarded and a fresh one is started, redrawing every random shock (the implicit-target direction is unchanged, since it does not depend on any draw).

For each accepted reduced-form draw we search over candidate orthogonal rotations (up to 500 candidates per draw, each a full pass through the sequential construction above) and retain the first that satisfies all restrictions; a draw is discarded if no candidate qualifies. We retain 10,000 accepted structural draws over a horizon of 24 quarters, with restrictions evaluated over the first 4 quarters. The acceptance rate is 67.8% (10,000 accepted from 14,754 reduced-form draws tried), indicating that the restriction set is informative but far from vacuous. All reported point estimates (impulse responses, historical decompositions, forecast-error variance decompositions) are posterior means with 16–84 percentile bands unless stated otherwise.

**A note on the sampling prior.** Two features of this construction warrant an explicit note. First, for the sign-restricted shocks, the sequential "uniform unit vector in the orthogonal complement" draw is exactly the Haar (rotationally invariant) measure on the rotation group of the relevant subspace, so this part of the scheme coincides with the standard rotation approach of Rubio-Ramírez et al. (2010). Second, in the presence of the exclusion (zero) restrictions—the contemporaneous zeros for the exchange-rate and oil shocks, together with the block-exogeneity zeros—a sequential null-space construction does not reproduce the prior that is *conditionally uniform* over the identified set; recovering that benchmark requires the importance-reweighting of Arias et al. (2018), which we do not apply. The draws therefore represent a particular, draw-order-dependent prior over admissible rotations. We view this as a deliberate, if implicit, prior choice rather than an error: as Baumeister and Hamilton (2015) emphasize, no prior over the set of admissible rotations is truly uninformative, so the conditionally-uniform benchmark holds no privileged status. Its practical footprint is in any case limited here, for three structural reasons: block exogeneity is imposed *exactly* through the domestic/global subspace split rather than by rejection; the implicit-target direction is deterministic and independent of any draw; and only four within-impact exclusions remain in a ten-variable system. Appendix A restates the full procedure as pseudocode. As a direct check on the prior's influence, we re-identify the model under permutations of the order in which the freely-rotated shocks are drawn and recompute the historical decomposition (Table A.1). The global–domestic split that carries our headline result is essentially unaffected: across orderings the surge-window and full-period global and domestic contributions move by at most 0.00 *p.p.* each on a surge-window base of about 5.17 *p.p.*. The implicit-target contribution—the object at the centre of the paper—is invariant to within about 0.002 *p.p.* in every window, and the domestic monetary-policy contribution remains small and positive under every ordering (at most 0.08 *p.p.* over the full period, and in the 0.06–0.25 *p.p.* range at the height of the surge). The prior's influence is confined to a reallocation of variance *among mutually correlated shocks within each block* at the finest ten-way disaggregation—individual global shocks shifting by up to about 0.28 *p.p.*, and the supply–demand lens by up to about 0.35 *p.p.*, in the surge window—which in every case preserves the sign and the ranking of the dominant contributions.[2]

# 4 Results and policy implications

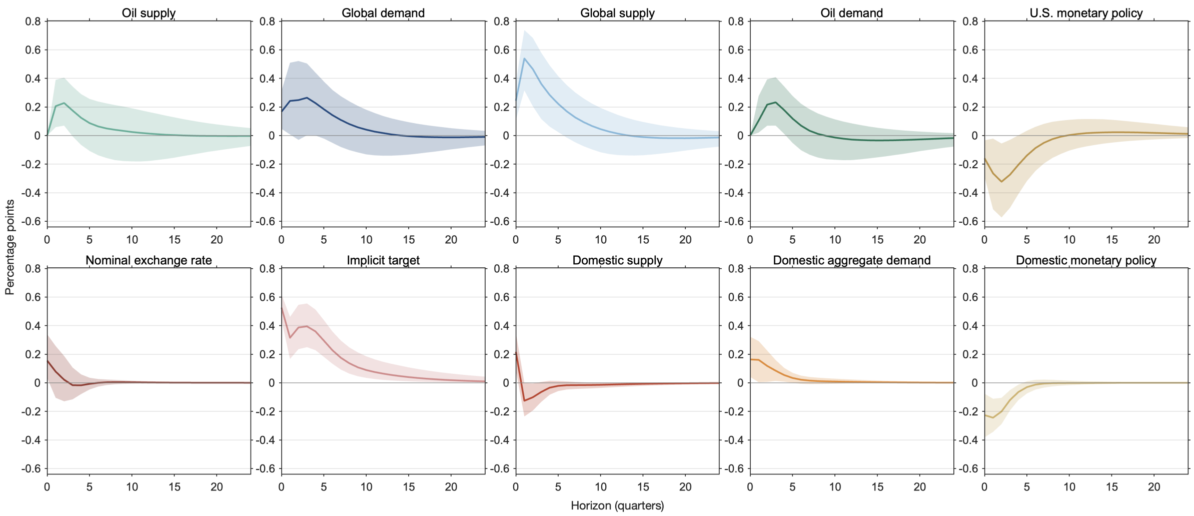
## 4.1 Impulse responses

Before decomposing history, we verify that the identified shocks transmit to inflation in economically sensible ways. Figure 2 plots the response of Costa Rican inflation to the ten structural shocks. The patterns accord with priors: global demand and global supply shocks raise domestic inflation persistently; a domestic monetary-policy tightening lowers inflation and appreciates the currency; an exchange-rate depreciation shock raises inflation with the expected pass-through profile; and the oil shocks feed into inflation with a short lag. Importantly for the results that follow, the *magnitude* of the inflation response to global shocks dominates that to the domestic monetary-policy shock at the horizons that matter for the historical decomposition.

These patterns line up with standard small-open-economy transmission channels rather than being imposed only through the identifying restrictions themselves. A domestic monetary tightening lowers inflation and appreciates the currency together; an exchange-rate depreciation passes through to inflation quickly, peaking on impact rather than with a delay; and the global demand and supply shocks move Costa Rican inflation in the same direction as the U.S. output gap or trading-partner

[2] The permutations are drawn from the *feasible* set: because the oil-supply shock carries two contemporaneous exclusions, it cannot be drawn as the last free shock in the global block without exhausting the available subspace—itself an illustration that zero restrictions constrain the admissible draw order. We permute the freely-rotated shocks within each block, holding fixed the deterministic implicit-target direction (drawn first) and the two residual supply shocks (the one-dimensional remainders). The figures are computed from 10,000 accepted draws per ordering, the same count as the baseline results; that the aggregate lenses are far more stable than their components (the surge-window global contribution moves by less than 0.01 *p.p.* while individual global shocks move by up to 0.28 *p.p.*) reflects a genuine within-block reallocation among correlated shocks, not sampling noise.

Figure 2: Response of Costa Rican inflation (`infCR`) to the ten identified structural shocks.




**Notes:** Posterior means with 16–84 percentile bands.

inflation that identify them, consistent with a price-taking small open economy importing rather than generating these disturbances.

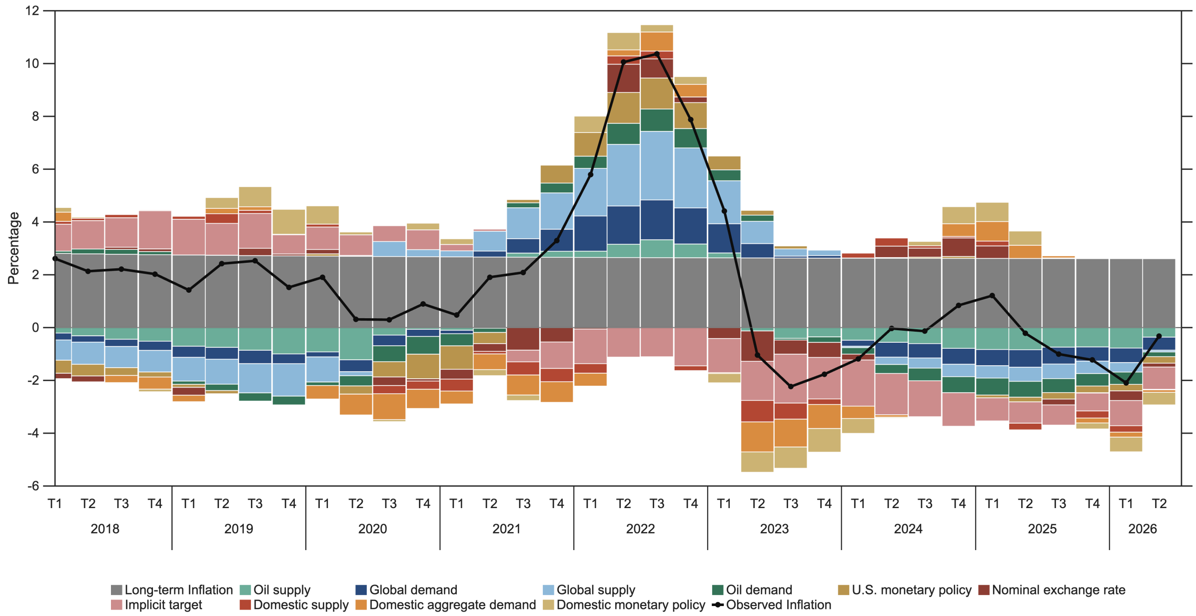
Global shocks are, on average, both larger and more persistent than domestic ones. The mean peak response of inflation is 0.32 *p.p.* for a global shock against 0.27 *p.p.* for a domestic shock, and two years after impact global shocks still carry 14% of their peak effect on average, versus 6% for domestic shocks. The pattern is not uniform across individual shocks, however, and the heterogeneity is informative. The single largest peak impact effect in the entire system belongs to the global supply shock (+0.53 *p.p.* one quarter after impact), narrowly ahead of the implicit-target shock (+0.53 *p.p.* on impact); the implicit-target shock is nonetheless, by a wide margin, the most persistent of the five domestic shocks, still carrying 30% of its peak effect two years out—the most persistent shock in the entire system, narrowly ahead of global demand (28%)—which is why we treat it separately from the other domestic disturbances in what follows. Domestic monetary policy sits at the other extreme: a comparatively modest peak (−0.23 *p.p.*) and the fastest decay of any shock in the system, with almost none of its peak effect (1%) remaining after two years—the transitory, quickly-reversed footprint expected of a systematic policy response rather than an independent driver of inflation.

## 4.2 Historical decomposition: all shocks

Figure 3 shows the full ten-shock historical decomposition of inflation over the IT period. Each bar decomposes the deviation of realized inflation from the long-term inflation into the cumulative contributions of the ten structural shocks.[3] The visual message is already clear: the large positive

[3]This long-term inflation is the model's baseline, which econometrically is the projection implied by initial conditions and the deterministic component. It can be interpreted as the level toward which inflation converges once the effects of shocks—that is, temporary disturbances, both global and domestic—have dissipated. It is important

Figure 3: Historical decomposition of Costa Rican inflation into all ten structural shocks, 2018-2026.




**Notes:** Bars show contributions to the deviation of inflation from its model-implied long-term baseline; the solid line shows observed inflation.

contributions during the 2021–2022 surge are concentrated in the global shocks, while the swing back into negative territory reflects both the fading of those global contributions and additional downward pressure from domestic shocks. Within the resulting 2023 initial-disinflation window, domestic shocks account for most of the negative inflation gap, before global forces reassert themselves in 2024–2026 (Lens 1 below develops this in full).

To quantify, Table 3 reports the average quarterly contribution of each shock over five windows: the full IT period (2018Q1–2026Q2), the inflation surge (2021Q4–2023Q1), an initial disinflation (2023Q2–2024Q1), a stabilization phase (2024Q2–2025Q2), and a second disinflation (2025Q3–2026Q2). Throughout this section we report posterior *means* rather than posterior medians for all point estimates of shock and group contributions.[4] During the surge, the three largest positive contributors are global supply (+2.00 *p.p.*), global demand (+1.27 *p.p.*), and U.S. monetary policy (+0.91 *p.p.*), with domestic aggregate demand essentially flat (+0.02 *p.p.*) per quarter. The domestic monetary-policy contribution is +0.25 *p.p.*.

to note that this long-run mean does not necessarily correspond to the inflation observed at any given point in time; in practice, inflation fluctuates around this level as a result of unexpected shocks with temporary effects on prices.

[4] Because the mean is a linear operator, it is exactly additive across every level of aggregation used below: the mean contributions of the ten individual shocks in Table 3 sum exactly to the corresponding grouped contributions in Table 4, which in turn sum exactly to the total deviation of inflation from its baseline, in every window. The posterior median does not share this property: the median of a sum of correlated random variables need not equal the sum of their individual medians, so a reader summing rows of Table 3 under a median-based reporting convention would generally not recover the corresponding entry of Table 4.

Table 3: Average quarterly contribution to the inflation gap by shock (p.p.)

| **Shock** | **2018–2026** | **Surge 2021Q4–2023Q1** | **Disinflation 2023Q2–2024Q1** | **Stabilization 2024Q2–2025Q2** | **Disinflation 2025Q3–2026Q2** |
|---|---|---|---|---|---|
| Global demand | −0.02 | +1.27 | +0.12 | −0.60 | −0.55 |
| Global supply | +0.12 | +2.00 | +0.32 | −0.43 | −0.36 |
| U.S. monetary policy | +0.00 | +0.91 | +0.08 | −0.03 | −0.25 |
| Domestic monetary policy | +0.07 | +0.25 | −0.76 | +0.41 | −0.32 |
| Oil (supply) | −0.37 | +0.39 | −0.34 | −0.72 | −0.65 |
| Oil (demand) | −0.11 | +0.60 | −0.07 | −0.53 | −0.41 |
| Implicit target | −0.32 | −1.21 | −1.66 | −1.18 | −0.81 |
| Domestic supply | −0.08 | −0.07 | −0.36 | +0.08 | −0.13 |
| Nominal exchange rate | −0.07 | +0.17 | −0.62 | +0.39 | −0.19 |
| Domestic aggregate demand | −0.22 | +0.02 | −0.89 | +0.32 | −0.10 |

**Notes:** Contributions are posterior-mean cumulative contributions to the deviation of inflation from its baseline, averaged over the indicated window.

## 4.3 Lens 1: global vs. domestic

The preceding subsection presented the full ten-shock historical decomposition. The following subsections reorganize those same structural contributions into a sequence of economically meaningful lenses. This section shows how aggregating the shocks along different dimensions can answer progressively more specific questions about the forces driving inflation without changing the underlying decomposition. Each lens is simply a linear aggregation of the same ten identified shock contributions and is therefore mutually consistent with the others by construction. We begin with the broadest distinction: whether inflationary pressures originated from global or domestic factors.

Aggregating the ten shocks into global (the five global shocks) and domestic (the five domestic shocks) blocks gives the sharpest summary of the paper's central result. Figure 4 and the top panel of Table 4 show that during the 2021Q4–2023Q1 surge, global factors contributed on average $+5.17\,p.p.$ per quarter to the inflation gap, while domestic factors were essentially flat ($-0.85\,p.p.$), making the surge almost entirely a global phenomenon. The transition to the sharp initial disinflation (2023Q2–2024Q1) reflected two forces. The global contribution fell by $5.06\,p.p.$, from $+5.17\,p.p.$ to $+0.11\,p.p.$, while the domestic contribution became $3.45\,p.p.$ more negative, moving from $-0.85\,p.p.$ to $-4.30\,p.p.$. Thus, the decline in inflation reflected both the fading of the global forces that drove the run-up and additional downward pressure from domestic shocks. Once the transition had occurred, however, domestic factors accounted for most of the negative inflation gap within the initial-disinflation window, with negative contributions from domestic demand, the exchange rate, the implicit target, and domestic monetary-policy shocks (Table 3). Global factors reassert themselves afterward, in the stabilization ($-2.31\,p.p.$) and second disinflation ($-2.23\,p.p.$) windows, while domestic factors stay essentially flat during stabilization ($+0.02\,p.p.$) before turning more negative again ($-1.54\,p.p.$). Over the full IT period the two blocks roughly offset ($-0.37\,p.p.$ global, $-0.61\,p.p.$ domestic), reflecting the pre-pandemic undershoot, the surge, and this more intricate reversal.

Figure 4: Historical decomposition of Costa Rican inflation: global vs. domestic factors, 2018–2026.

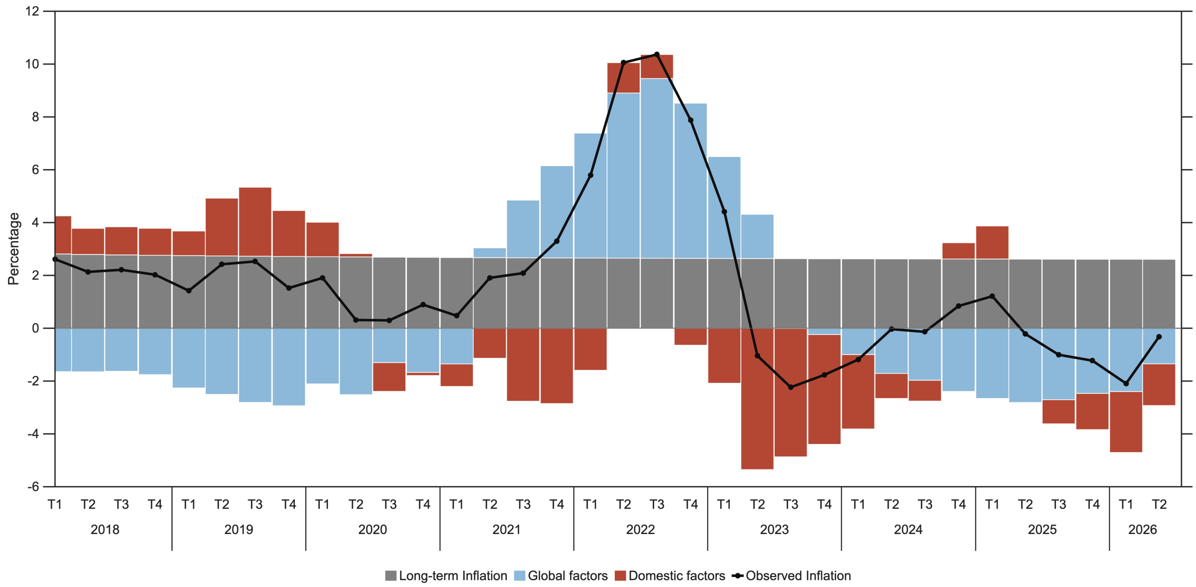



Table 4: Average quarterly contribution to the inflation gap by lens (p.p.)

| | **2018–2026** | **Surge 2021Q4–2023Q1** | **Disinfl. 2023Q2–2024Q1** | **Stabiliz. 2024Q2–2025Q2** | **Disinfl. 2025Q3–2026Q2** |
|---|---|---|---|---|---|
| | | | ***Lens 1: global vs. domestic*** | | |
| Global factors | −0.37 | +5.17 | +0.11 | −2.31 | −2.23 |
| Domestic factors | −0.61 | −0.85 | −4.30 | +0.02 | −1.54 |
| | | | ***Lens 2: supply vs. demand*** | | |
| Demand factors | −0.28 | +3.04 | −1.52 | −0.43 | −1.63 |
| Supply factors | −0.71 | +1.28 | −2.67 | −1.86 | −2.14 |
| | | | ***Lens 3: supply/demand by region*** | | |
| Global demand | −0.13 | +2.77 | +0.13 | −1.16 | −1.22 |
| Global supply | −0.24 | +2.40 | −0.02 | −1.15 | −1.01 |
| Domestic demand | −0.15 | +0.27 | −1.65 | +0.73 | −0.42 |
| Domestic supply | −0.46 | −1.12 | −2.65 | −0.71 | −1.12 |
| | | | ***Lens 4: monetary policy & exchange rate vs. rest*** | | |
| Domestic monetary policy | +0.07 | +0.25 | −0.76 | +0.41 | −0.32 |
| Nominal exchange rate | −0.07 | +0.17 | −0.62 | +0.39 | −0.19 |
| All other factors | −0.99 | +3.91 | −2.81 | −3.09 | −3.27 |

**Notes:** Each lens is a linear aggregation of the same ten structural contributions; blocks within a lens sum to the total inflation gap. Posterior means, averaged over the indicated window.

These historical contributions describe the shocks that actually occurred along the realized sample path; a complementary, sample-independent check is given by the forecast-error variance decomposition (FEVD) reported in Appendix B. Figure B.1 shows the full ten-shock FEVD of inflation, and aggregating the same ten shocks into the global/domestic split used in this lens (Figure B.6) confirms the pattern unconditionally: the global block already accounts for roughly

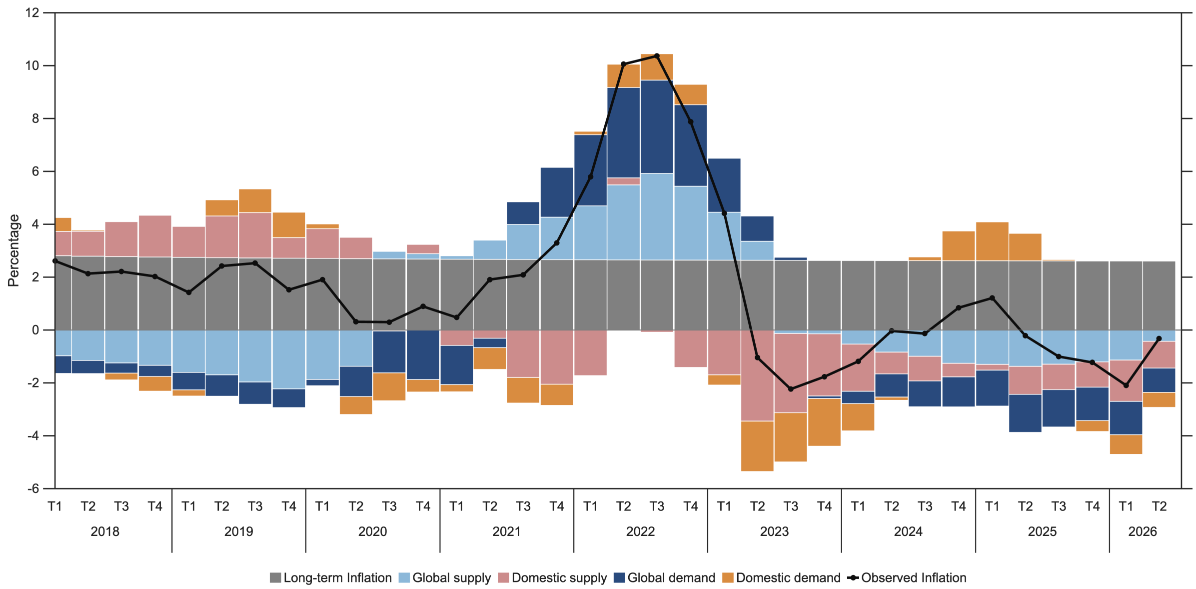
24% of the variance of the inflation forecast error on impact, rising to about 69% at the five-year horizon, the same global dominance documented above for the realized sample, now shown to hold independently of which shocks happened to be large historically. The identical ten-shock FEVD is aggregated instead into the supply/demand split of Lens 2 in Figure B.7, so the two groupings, this section's global/domestic split and Lens 2's supply/demand split, whose intersection defines Lens 3, that are built from the same underlying variance decomposition and are therefore directly comparable, both here and in the historical decomposition of Table 4.

### 4.4 Lens 2: supply vs. demand

Each shock is classified as demand-type or supply-type by the same comovement criterion used to identify it in Section 3.2: a shock that moves inflation and the relevant output gap in the *same* direction is demand-type, while one that moves them in *opposite* directions is supply-type. For seven of the ten shocks the label follows directly from their own identifying restrictions in Table 2. Oil supply and global supply raise inflation while lowering the U.S. output gap, and oil demand and global demand raise inflation and the U.S. output gap together (these four are global-origin shocks, so it is the U.S. gap rather than Costa Rica's that co-moves with inflation at identification); domestic supply raises inflation while lowering the Costa Rican gap, domestic demand raises both together, and domestic monetary policy lowers both together (so "supply" or "demand" is already built into how each of these seven was identified). The remaining three shocks (U.S. monetary policy, the nominal exchange rate, and the implicit target) are not pinned down this way, because their restrictions do not jointly sign inflation and an output gap, so they are assigned by the same logic applied to the shock's economic type rather than to a restricted comovement: U.S. monetary policy is demand-type, since a global tightening operates on Costa Rican inflation through the same demand channel as its domestic counterpart; the exchange-rate and implicit-target shocks are supply-type, since both move inflation directly (via pass-through and the perceived nominal anchor, respectively) without a corresponding activity effect.

Grouping instead by economic nature, demand-type vs. supply-type disturbances, regardless of origin, shows that the surge was *demand-led* ($+3.04\,p.p.$ per quarter) with a smaller supply contribution ($+1.28\,p.p.$). Within the initial-disinflation window, the negative inflation gap was more *supply*-led (supply $-2.67\,p.p.$, demand $-1.52\,p.p.$), and the later stabilization and second-disinflation windows remain supply-led as well ($-1.86\,p.p.$ and $-2.14\,p.p.$ versus $-0.43\,p.p.$ and $-1.63\,p.p.$ for demand). This is consistent with a narrative in which the global demand boom of 2021–2022 drove the initial run-up, the subsequent decline reflected both fading global pressures and more negative domestic contributions, and the composition of the inflation gap during the 2023 initial-disinflation window was dominated by domestic supply and demand forces (Lens 1 above). From 2024 onward, the normalization of *global* demand and supply chains, together with falling commodity prices, again became the dominant force pulling inflation below target.

Figure 5: Historical decomposition of Costa Rican inflation: supply and demand by region (global vs. domestic), 2018–2026.



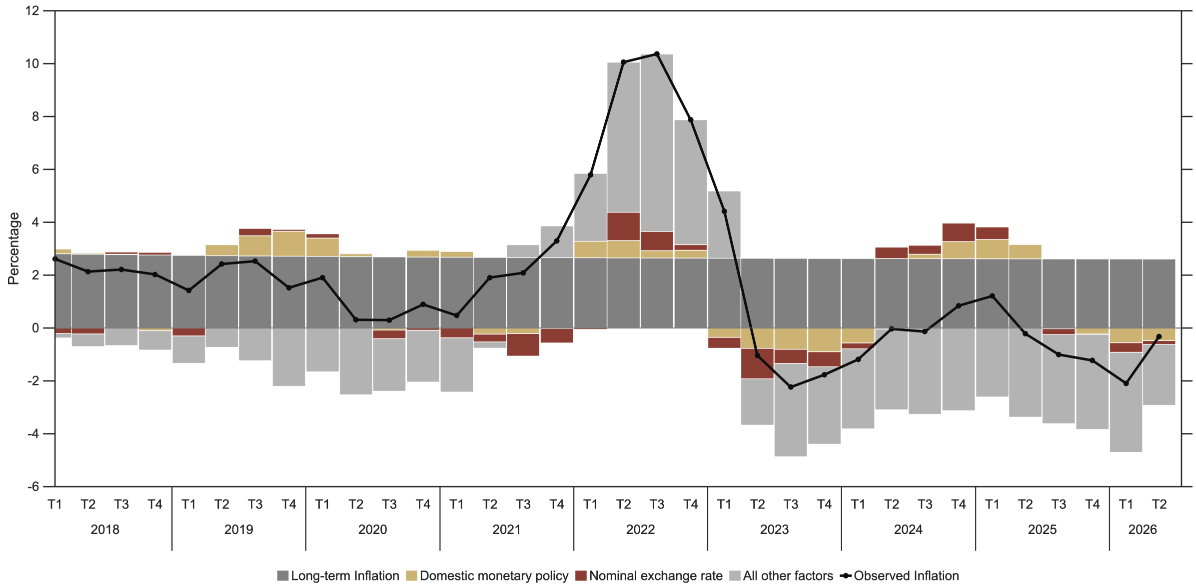

## 4.5 Lens 3: supply/demand by region

Crossing the two previous lenses isolates the single most important cell during the surge: *global demand* contributed $+2.77\,p.p.$ per quarter, the largest of the four region-by-type contributions, with global supply second ($+2.40\,p.p.$); domestic demand and domestic supply were comparatively small over the same window ($+0.27\,p.p.$ and $-1.12\,p.p.$). The composition of the inflation gap inverts in the initial-disinflation window: domestic supply ($-2.65\,p.p.$) and domestic demand ($-1.65\,p.p.$) are now the largest contributors, while global demand ($+0.13\,p.p.$) and global supply ($-0.02\,p.p.$) are both essentially flat. These figures describe the level of the inflation gap within that window; the transition into it also reflected the substantial decline in the previously positive global contribution documented in Lens 1. Global forces reassert themselves in the stabilization and second-disinflation windows, when global demand ($-1.16\,p.p.$, $-1.22\,p.p.$) and global supply ($-1.15\,p.p.$, $-1.01\,p.p.$) are again among the largest negative contributors, on a par with domestic supply in the same windows ($-0.71\,p.p.$, $-1.12\,p.p.$). Figure 5 displays the four region-by-type contributions.

## 4.6 Lens 4: monetary policy and the exchange rate vs. the rest

The final lens speaks most directly to the evaluation of the regime. We isolate the domestic monetary-policy shock and the nominal exchange rate, while grouping all remaining shocks, including U.S. monetary policy, into a residual block (Figure 6 and the bottom panel of Table 4). Domestic monetary policy contributed only $+0.07\,p.p.$ per quarter on average over the full period. Its contribution rose to $+0.25\,p.p.$ during the surge, turned to $-0.76\,p.p.$ during the initial disinflation, rebounded to $+0.41\,p.p.$ during stabilization, and reached $-0.32\,p.p.$ in the second disinflation. These contributions were modest relative to the multi-percentage-point movements in the residual

Figure 6: Historical decomposition of Costa Rican inflation: monetary policy and the nominal exchange rate vs. all other factors, 2018–2026.




"all other factors" block, which contributed +3.91 *p.p.* during the surge alone and also includes the U.S. monetary-policy shock. Table 3 further shows that domestic monetary policy was one of five shocks contributing to the negative domestic component within the initial-disinflation window. The exchange-rate contribution is small throughout and, if anything, disinflationary during the surge (reflecting a period of colón appreciation). In short, neither monetary policy nor the exchange rate is the proximate driver of the level of inflation in any window; the residual is dominated by global forces during the surge, by domestic supply, demand, and anchor shocks during the initial-disinflation window, and by global forces again during the stabilization and second-disinflation windows (Table 4).

Appendix B corroborates this reading from the variance side. The nominal exchange-rate shock explains only 22.2% of the forecast-error variance of `tcn` on impact, falling to 15.8% at the five-year horizon (Figure B.2), with most of the remainder attributable to the Costa Rican output gap and inflation rather than to its own shock, consistent with a managed float that reacts to domestic conditions more than it moves on independent exchange-rate news. The domestic monetary-policy shock is a smaller source of variance still for the policy rate itself: it accounts for just 14.7% of the forecast-error variance of `tpm` on impact and a mere 1.5% at the five-year horizon (Figure B.5), with most of `tpm`'s variation explained instead by the output gap, inflation, and long-run expectations—i.e., by the systematic, rule-like component of policy rather than by exogenous policy shocks. The same is true for the real economy at longer horizons: domestic monetary policy accounts for 15.0% of the forecast-error variance of the Costa Rican output gap on impact, falling to 5.4% at the five-year horizon (Figure B.4), by which point it is smaller than the oil-demand shock (9.1%) and well below the implicit-target shock (20.8%), whose own share of `gapCR`'s variance grows steadily with the horizon. Together these FEVDs are the variance-decomposition counterpart of the historical decomposition above: monetary policy's modest contribution to the level of inflation reflects that most of what the policy rate does, and most of what moves the real economy, is a systematic response to domestic and global conditions rather than an independent driver of either.

### 4.7 The implicit target and long-run expectations

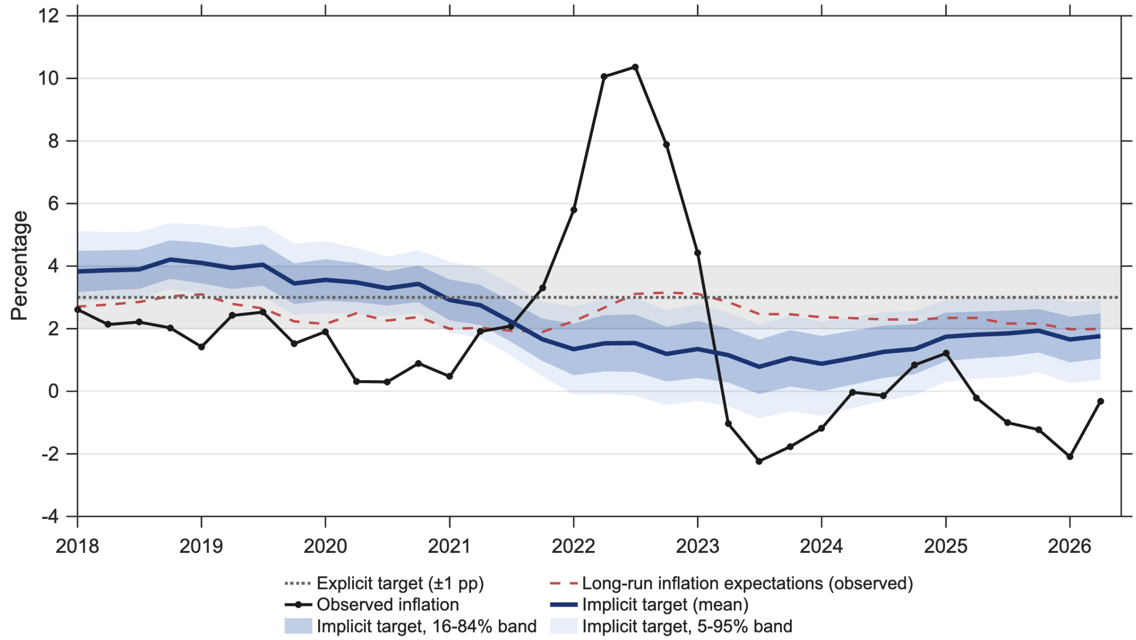
The preceding lenses explain the *level* of inflation and locate monetary policy as a quantitatively small direct contributor. This subsection turns to a complementary indicator of the regime's performance: the *implicit target*. Recall from Section 3.2 that the implicit-target shock is identified as the domestic disturbance that maximizes the forecast-error variance of long-run (60-month) inflation expectations. We construct the corresponding implicit target as the level toward which inflation would settle if driven only by its estimated long-run (deterministic) mean and the identified implicit-target shock. Formally, it is the model's deterministic inflation path plus the historical contribution of the implicit-target shock to inflation, reported with 16–84 (and 5–95) posterior bands. This series is interpreted as a model-based estimate of the economy's perceived long-run nominal anchor, shaped by the private sector's reading of policy. Comparing it with the BCCR's *explicit* target provides a diagnostic of the degree of alignment between the perceived and announced objectives. The explicit target itself has stepped down over the sample, from 5% (±1 pp) before 2010 to 4% (±1 pp) through 2015 and 3% (±1 pp) since—and has been 3% (±1 pp) throughout the inflation-targeting period that is the focus of this paper.

Figure 7 makes the comparison. Both the implicit target and observed long-run expectations moved considerably less than realized inflation, which ranged from +10.4% in 2022Q3 to −2.2% in 2023Q3. Their behavior is not identical, however. Observed long-run expectations remained within a narrow 1.9–3.2% range, whereas the posterior-mean implicit target ranged from 0.8% to 4.2% and drifted gradually downward from 2018, falling below the lower edge of the BCCR's tolerance band during part of the IT period. The implicit target did not rise in step with the 2021–2023 inflation surge, which indicates resilience against upward deanchoring, but its subsequent downward drift also means that the perceived anchor was not perfectly aligned with the explicit target throughout the sample.

The historical decomposition quantifies the economically meaningful contribution of this downward movement to inflation. The implicit-target shock contributed $-1.21\,p.p.$ per quarter during the surge, $-1.66\,p.p.$ during the initial-disinflation window, and $-1.18\,p.p.$ during stabilization (Table 3). These are non-negligible disinflationary contributions, particularly during 2023Q2–2024Q1, rather than evidence that shifts in the perceived target were irrelevant for realized inflation.

Consistent with its max-FEV identification, the implicit-target shock explains 80.2% of the forecast-error variance of `expInf60` on impact and 57.7% at the five-year horizon (Figure B.3, Appendix B). These large shares are an implication of the identification criterion and therefore should not be interpreted as independent corroboration of anchoring. They confirm instead that the max-FEV procedure isolates a distinct long-run-expectations component from the other nine shocks in the model.

Figure 7: The implicit target versus the explicit target.




**Notes:** The implicit target is the model's deterministic long-run inflation path plus the estimated contribution of the implicit-target (max-FEV expectations) shock to inflation, with posterior 16–84 and 5–95 percentile bands. The explicit target is the BCCR's official step-down band (5%, then 4%, then 3%, each ±1 pp, constant at 3% throughout the IT period shown). Observed long-run (60-month) inflation expectations and realized headline inflation are overlaid.

The resulting evaluation is therefore nuanced. Long-run expectations remained near the announced objective and neither expectations nor the implicit target rose with the global inflation surge. At the same time, the implicit target drifted below the tolerance band and its shock made a material disinflationary contribution. The comparison with the explicit target remains a useful policy indicator, but it points to relative resilience rather than complete stability of the perceived nominal anchor.

## 4.8 Discussion: what the decomposition says about policy

The results resolve an apparent paradox. Read naïvely, a historical decomposition in which domestic monetary-policy shocks contribute a fraction of a percentage point to inflation, while global shocks contribute several, might suggest that monetary policy in Costa Rica is nearly irrelevant to inflation. That inference would be wrong, and understanding why is the purpose of the discussion that follows.

A historical decomposition attributes movements in inflation to identified *shocks*: unanticipated, orthogonal innovations. The monetary-policy shock is the component of policy that is *not* a systematic response to the state of the economy, in effect, policy surprises. Under a credible IT regime run by a central bank that responds predictably to shocks and communicates clearly, policy surprises should be small *by construction*, and hence contribute little to the decomposition. The bulk of what monetary policy does –leaning against demand pressures, responding to the exchange rate, and above all anchoring expectations –operates through the *systematic* reaction function, which the decomposition folds into the endogenous propagation of the other shocks rather than isolating as a "monetary" contribution. The small monetary-policy-shock contribution is therefore not evidence of impotence; it is consistent with a central bank that rarely surprised markets.

The implicit-target result helps assess, but does not conclusively settle, this interpretation. Neither observed long-run expectations nor the implicit target rose in step with the 2022 inflation surge, which weighs against an upward deanchoring narrative. The two measures nevertheless differ in the subsequent period. Observed expectations remained within a narrow range, while the implicit target drifted downward and fell below the tolerance band during part of the sample (Section 4.7). The evidence therefore points to relative resilience of long-run expectations rather than perfect stability of the perceived anchor. The modest exchange-rate contribution during the surge coexists with this relative stability, but the decomposition alone does not establish that anchoring caused pass-through to remain contained.

One episode qualifies this reading and is worth addressing directly. The transition to the sharp 2023 disinflation (Section 4) reflected both a 5.06 *p.p.* decline in the global contribution and a 3.45 *p.p.* decline in the domestic contribution. Within the resulting initial-disinflation window, however, domestic factors accounted for most of the negative inflation gap. The domestic monetary-policy *shock* is larger in this window than in any other ($-0.76$ *p.p.* per quarter), but it remains a small part of the change in the domestic contribution, most of which shows up as more negative contributions from domestic demand and supply, the exchange rate, and the implicit target, consistent with an aggressive but *anticipated* policy tightening (the BCCR's TPM hike from 0.75% to 9% over 2022, documented in Section 5.1) working through the economy with a lag, rather than a fresh policy surprise. The episode is, in other words, systematic policy doing its job—just with a domestic rather than global fingerprint.

Two additional exercises place this reading in context. First, the forecast-error variance decompositions in Appendix B show that the domestic monetary-policy and exchange-rate shocks explain only a small share of the variance of their own respective variables—evidence that most of what the policy rate and the exchange rate do is systematic response rather than exogenous shock, independent of which shocks happened to be large in the historical sample. Second, Section 5.1 compares the identified shocks with events documented in the BCCR's Monetary Policy Reports, an external record that plays no role in estimation or identification. The comparison supports the interpretation of selected global episodes but is mixed for domestic shocks, most notably because the large domestic-demand shock in 2023Q2 runs counter to the BCCR's contemporaneous assessment. These exercises are informative about particular mechanisms but do not constitute external validation of the full identification scheme.

Two implications for how the BCCR interprets and communicates its record follow directly. First, the distance between realized inflation and the target is a poor scorecard for policy in an economy as open as Costa Rica's: it was breached in both directions by forces the central bank could not have offset without imposing large real costs, and its breach carries little information about the conduct of policy. The implicit target and observed long-run expectations provide a more informative complementary scorecard. By this measure, the regime displayed resilience against upward deanchoring during the surge, together with a subsequent downward drift that should not be overlooked. Second, communication should make the imported nature of inflation volatility explicit, distinguishing the component of inflation that policy can influence at policy-relevant horizons from the larger, external component it cannot, while reporting the behavior of the implicit target and observed expectations as evidence on the degree of alignment between the perceived and explicit objectives.

Policy communication deserves separate emphasis, because the evidence in this paper suggests the BCCR already possesses the raw material for a more precise version of the message it delivers today. Its own Monetary Policy Reports narrate, quarter by quarter, the shocks it judges responsible for the inflation outturn. Some prominent global episodes align with the identified shocks, although the comparison is weaker for the 2023 domestic-demand shock (Section 5.1). Thus, the qualitative story that a given surprise was imported rather than a policy failure is not new to the institution's communication. What is missing is a single, quantitative anchor that lets that qualitative narrative be checked over time, rather than reconstructed anew each quarter: the implicit target developed here plays exactly that role. Rather than defending each quarter's deviation from the 3% band with a fresh narrative account, the BCCR could report the estimated implicit target alongside the explicit one, making the degree of alignment between the perceived and announced objectives falsifiable and comparable across episodes. Doing so would also clarify, ex ante rather than ex post, which global commodity and demand shocks the regime may absorb without an immediate policy response, and which developments in the perceived target warrant closer policy attention. This would turn the distinction drawn by the model into an operational communication tool without treating every estimated movement in the implicit target as an automatic call for a policy response.

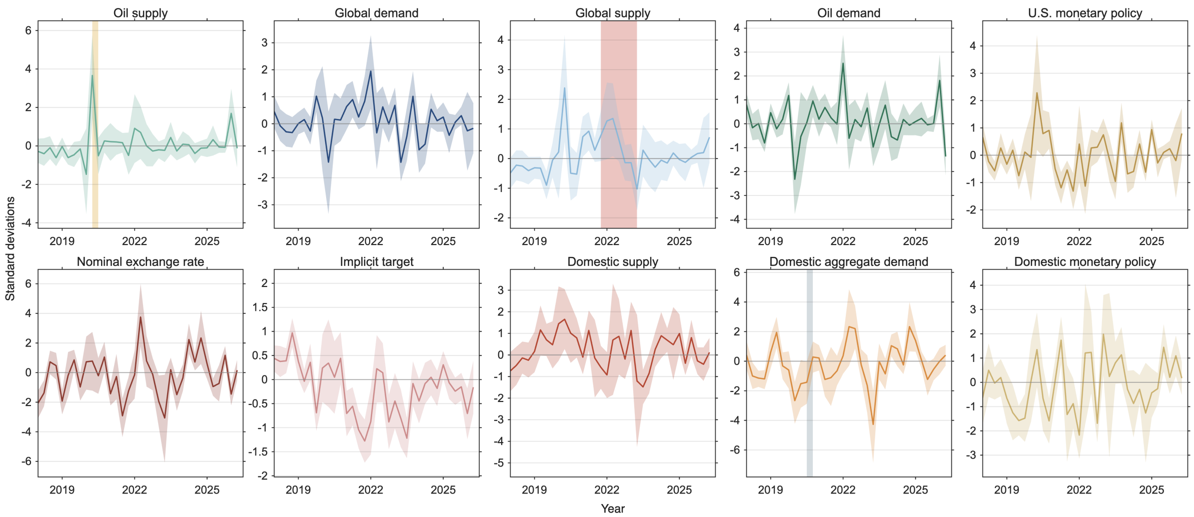
# 5 Model assessment and robustness

## 5.1 Narrative comparison with the BCCR's Monetary Policy Reports

Sign-restricted SVARs are identified from statistical restrictions alone, so, as Fry and Pagan (2011) emphasize, an identified shock's economic content is an interpretation rather than a guarantee. We therefore compare the model's quarterly historical decomposition with the chronology of unanticipated events documented by the BCCR in its *Informe de Política Monetaria* (IPM), published roughly every quarter. These narratives play no role in estimation or identification and provide a qualitative external benchmark. Agreement in direction and timing is reassuring, while disagreement identifies episodes in which the structural interpretation should be treated more cautiously. The exercise is a narrative comparison, not an additional identification test.

For each quarter of the IT sample we take the shock with the largest-magnitude posterior-mean contribution to the inflation gap (the same contributions underlying Table 3) and compare it, in direction and timing, to the surprise events listed in the IPM published nearest that quarter.

Figure 8: Posterior-mean structural shocks, 2018–2026.




**Notes:** Posterior means with 16–84 percentile bands, in standard deviations. Shaded windows mark selected narrative episodes discussed in the text and Figure 1; they are illustrative rather than exhaustive and are shown only on the panel of the shock to which each episode is compared. Shocks identified around 2020 should be read with additional caution: the sheer density of overlapping COVID-19 disturbances—simultaneous domestic lockdown measures and global supply-chain and demand disruptions—makes it difficult for the sign-restriction algorithm to cleanly separate domestic from global, or demand from supply, channels in that window, so the magnitudes attributed to individual shocks in 2020 are less cleanly identified than elsewhere in the sample.

Figure 8 plots the identified shocks themselves. Table 5 reports selected matches and, separately, the complete set of structural shocks exceeding four standard deviations during the IT period.

Two matches are especially informative. First, the 2020Q2–Q3 window combines two overlapping COVID-era developments documented across the BCCR's contemporaneous reports: the *oil supply* shock in 2020Q2, coinciding with the IPM Abril 2020's account of an oil-price war among exporting countries that flooded the market just as pandemic restrictions collapsed global demand, and the *domestic aggregate demand* shock in 2020Q3, coinciding with the IPM Octubre 2020's account of domestic demand contracting 4.8% and household consumption 5.8% that quarter, driven by the sanitary lockdown and border closure that abruptly ended tourism growth. As Figure 8's notes flag, both matches should be read with some caution: 2020 crowds together a national lockdown, a global demand collapse, and a global supply disruption within one or two quarters, and disentangling which of several simultaneous COVID-19 shocks is doing the work is harder here than in any other episode in the sample. Second, the *global supply* shock dominates every single quarter of the 2021Q4–2023Q1 surge, also visible in Figure 8, coinciding with the IPM's own account of pandemic-era shipping-cost and supply-chain bottlenecks and, subsequently, the "stagflationary shock" to commodity and agricultural-input prices that the BCCR explicitly attributes to the Russia-Ukraine invasion—both described by the BCCR as adverse cost-push disturbances to the same block the model identifies as global.

The observed 2022 monetary tightening is informative about the distinction between policy actions and policy shocks, but we do not treat it as a narrative match in Table 5. The IPM Octubre

Table 5: Narrative comparison: selected matches and extreme structural shocks

| **Quarter** | **Documented event or assessment (IPM)** | **Identified shock** | **Model statistic** |
|---|---|---|---|
| *Panel A. Selected narrative matches* | | | |
| 2020Q2 | Oil-price war among exporting countries floods the market as pandemic demand collapses[a] | Oil supply | $-1.22\,p.p.$ |
| 2020Q3 | COVID-19 lockdown and border closure: domestic demand contracts 4.8%, household consumption 5.8%[b] | Domestic aggregate demand | $-0.98\,p.p.$ |
| 2021Q4–2023Q1 | Pandemic supply-chain bottlenecks and shipping-cost surge, compounded by the Russia–Ukraine "stagflationary shock"[c] | Global supply | $+1.38$ to $+2.60\,p.p.$ |
| *Panel B. All structural shocks exceeding four standard deviations* | | | |
| 2022Q2 | Foreign-exchange-market pressure intensifies and exchange-rate volatility nearly doubles[d] | Nominal exchange rate | $+4.1\sigma$ |
| 2023Q2 | Domestic activity accelerates; disinflation is attributed to fading global supply pressure, colón appreciation, and base effects[e] | Domestic aggregate demand (not corroborated) | $-4.8\sigma$ |

**Notes:** Panel A reports posterior-mean contributions to the inflation gap in percentage points. Panel B reports posterior-median structural shocks in standard deviations and includes every realization exceeding four standard deviations during the IT period. [a] IPM Abril 2020, p.16; [b] IPM Octubre 2020, pp.52–53; [c] IPM Enero 2022, p.32, and IPM Abril 2022, p.10; [d] IPM Julio 2022; [e] IPM Julio 2023.

2022 documents that the BCCR increased the TPM from 0.75% to 9% in response to the inflation surge. By contrast, the historical decomposition reports the cumulative contribution of identified monetary-policy innovations to inflation, which is positive in each quarter of 2022 ($+0.62\,p.p.$, $+0.66\,p.p.$, $+0.28\,p.p.$, and $+0.30\,p.p.$). The observed policy-rate increase and the cumulative inflation contribution are therefore different objects and cannot be used to validate one another. The episode is nevertheless consistent with much of the observed rate increase representing a systematic response to inflation rather than a sequence of contractionary policy surprises.

To reduce the selectivity inherent in Panel A, Panel B applies a simple rule: it includes every posterior-median structural shock exceeding four standard deviations during the IT period and asks whether each coincides with a documented IPM event, regardless of whether that shock is also the *dominant* contributor to the inflation gap in Table 5. Two realizations in the IT period clear this threshold, with mixed results. The nominal exchange-rate shock reaches +4.1 standard deviations in 2022Q2; the IPM Julio 2022 reports that pressure in the foreign-exchange market "intensified...during the second quarter of 2022," with the exchange rate's volatility nearly doubling quarter on quarter, driven by higher dollar demand for oil imports and pension-fund positioning—a distinct episode from the TPM tightening documented in the same report and discussed above, and a clear counterpart in the narrative record. The domestic aggregate-demand shock reaches −4.8 standard deviations in 2023Q2, but here the narrative record does not corroborate the shock's own content as cleanly: the IPM Julio 2023 instead reports that domestic economic activity *accelerated* that quarter and attributes the disinflation to the dissipation of the earlier global supply shock, the colón's appreciation since mid-2022, and base effects, rather than to weak domestic demand. We flag this discrepancy rather than force a reading the source material does not support; a statistically extreme realization need not always coincide with a clean narrative counterpart, and this is one case where the sign-restricted algorithm attributes a large residual to a shock whose own documented story runs the other way.

We treat this exercise as a mixed qualitative comparison, not a formal validation test. The matches in Panel A were selected for their clarity from a qualitative reading of every IPM over the sample, rather than from a systematic quarter-by-quarter classification. Panel B is exhaustive under its four-standard-deviation threshold and produces mixed evidence: one of the two extreme shocks has a clear narrative counterpart, while the other does not. Several documented surprises also have no clean counterpart in a single dominant shock. Smaller idiosyncratic events, such as the April 2022 cyberattack on the Ministry of Finance, may not be large enough relative to simultaneous disturbances to be individually identifiable. The selected matches are useful for interpreting particular episodes, but they should not be read as general external validation of the full identification scheme.

### 5.2 Diagnostics and robustness

Several checks support the reading above. *Reduced-form stability:* 99.4% of post-burn draws are stable, with a median spectral radius of 0.90, so the decomposition is not driven by near-explosive dynamics. *Identification informativeness:* the 68% structural acceptance rate indicates that the restriction set materially narrows the identified set without being degenerate, and the failure-reason tabulation (available on request) shows rejections spread across restrictions rather than concentrated on any single restriction. *Lens consistency:* because every lens is a linear aggregation of the same structural contributions, the blocks within each lens sum to the same total inflation gap; the qualitative conclusion (global dominance, limited monetary-policy role) is invariant to the aggregation chosen, which is itself a robustness property.

We flag the natural caveats. First, sign-restricted SVARs identify a *set*, and reported point estimates need not correspond to a single admissible model Fry and Pagan (2011); we therefore emphasize the sign and relative magnitude of contributions rather than point precision, and the qualitative story is stable across the posterior. Second, the choice of global block, the exchange-rate transformation (percentage change vs. log level), and the lag length are modelling decisions; unreported runs varying these leave the central conclusion intact. Sections 5.2.1 and 5.2.2 report two such checks in detail, using an alternative inflation measure and an alternative data-aggregation convention, respectively. Third, the historical decomposition is defined relative to a model baseline, so contributions should be read as *deviations* from that baseline rather than as a decomposition of the raw inflation level.

#### 5.2.1 Robustness: core inflation as the response variable

As a further check, we reestimate the full model with the BCCR's IEF core-inflation indicator in place of headline CPI inflation, keeping every other variable, restriction, and hyperparameter unchanged. Reduced-form and structural diagnostics are essentially unchanged (99.7% stability, 72.5% structural acceptance). Three results replicate. First, the global dominance of the inflation *level* holds directionally but is smaller in magnitude at short horizons: the unconditional FEVD global-block share is 12% on impact, rising to 67% at the five-year horizon (versus 24–69% for headline CPI), and the average quarterly global contribution during the 2021Q4–2023Q1 surge is $+2.37\,p.p.$ (versus $+5.17\,p.p.$ for headline)— consistent with core inflation excluding the volatile food and energy components most directly exposed to global commodity prices. Second, the limited role of domestic monetary-policy shocks is essentially unchanged: the shock contributes $+0.16\,p.p.$ per quarter during the surge (versus $+0.25\,p.p.$ for headline), and its own-shock FEVD share for the policy rate itself falls from 13.7% on impact to 1.9% at the five-year horizon (versus 14.7% to 1.5% for headline)—the same signature of systematic, rule-like policy. Third, as expected under the max-FEV identification, the implicit-target shock remains the dominant driver of the forecast-error variance of long-run expectations (87% on impact and 63% at the five-year horizon, versus 80% and 58% for headline). This shows that the identified max-FEV component is not sensitive to replacing headline inflation with a less volatile price index; it is not an independent test of expectations anchoring. Appendix C reports the full set of figures and a focused mean-contribution comparison for this alternative specification.

#### 5.2.2 Robustness: within-period mean aggregation

As a further check on a modelling decision noted above, we reestimate the full model using the within-period mean, rather than the end-of-quarter value, to aggregate higher-frequency source series to the model's quarterly frequency, applied uniformly across every daily-to-monthly and monthly-to-quarterly retiming step in the data pipeline (Section 2), keeping every variable, restriction, and hyperparameter unchanged. Reduced-form and structural diagnostics remain healthy under this alternative convention (98.5% stability, 93.7% structural acceptance, versus 99.4% and 67.8% at baseline), so the change in aggregation does not degrade identification. The paper's central results are essentially unaffected. The global–domestic split barely moves: the average quarterly global contribution during the 2021Q4–2023Q1 surge is $+5.41\,p.p.$ (versus $+5.17\,p.p.$ at baseline) and the domestic contribution is $-1.09\,p.p.$ (versus $-0.85\,p.p.$), with the same sign and order of magnitude over the full sample too ($-0.39\,p.p.$ global and $-0.62\,p.p.$ domestic, versus $-0.37\,p.p.$ and $-0.61\,p.p.$). The implicit target is essentially invariant to this choice, moving by no more than $0.02\,p.p.$ in either window ($-0.32\,p.p.$ versus $-0.32\,p.p.$ over the full sample; $-1.23\,p.p.$ versus $-1.21\,p.p.$ during the surge), and domestic monetary-policy shocks remain small throughout

(+0.07 *p.p.* versus +0.07 *p.p.* full-sample; +0.26 *p.p.* versus +0.25 *p.p.* surge). The supply–demand lens moves somewhat more—by up to about 0.34 *p.p.* in the surge window, as mass reallocates between the supply and demand components of the global block—but it preserves the sign and ranking of every contribution. Appendix D reports the corresponding figures.

## 6 Conclusion

We have asked what the behaviour of inflation since the consolidation of inflation targeting in 2018 reveals about the conduct of monetary policy in Costa Rica, and answered with a ten-variable Bayesian SVAR that combines block exogeneity, sign, zero, and max-FEV restrictions. Three findings cohere into a single reading. The *level* of inflation over 2018–2026 was a *global* phenomenon during its 2021Q4–2023Q1 surge: global demand and supply shocks drove it (together on the order of +3.3 *p.p.* per quarter of the inflation gap), while domestic factors were essentially flat. The reversal that followed was more intricate than a simple mirror image. The transition to the initial disinflation reflected both the fading of the earlier global contribution and additional downward pressure from domestic factors. Within the initial-disinflation window, domestic factors, including the exchange rate, accounted for most of the negative inflation gap, before global forces reasserted themselves in a later stabilization and second disinflation. Domestic monetary-policy *shocks* contributed little to the level of inflation throughout. The implicit target and observed long-run expectations were both considerably more stable than realized inflation, but they did not convey identical signals. Observed expectations remained within a narrow 1.9–3.2% range, while the model-implied target ranged from 0.8% to 4.2%, drifted below the tolerance band, and made a non-negligible disinflationary contribution, particularly during 2023Q2–2024Q1.

Several additional exercises place these findings in perspective. Forecast-error variance decompositions (Appendix B) provide a sample-independent check on the inflation results: global shocks account for roughly 24%–69% of the variance of the inflation forecast error, while the domestic monetary-policy and exchange-rate shocks explain only a small share of the variance of their own respective variables. The implicit-target shock accounts for over half the variance of long-run expectations at every horizon, as expected from its max-FEV construction; this verifies the intended identification but is not an independent test of anchoring. The comparison with the BCCR's Monetary Policy Reports supports the interpretation of selected global episodes but provides mixed evidence overall, including a clear discrepancy for the large domestic-demand shock in 2023Q2 (Section 5.1). Reestimating the model with the BCCR's core-inflation indicator (IEF) in place of headline CPI, holding every other variable and restriction fixed, replicates all three findings above, with the global contribution to the 2021Q4–2023Q1 surge scaling down from +5.17 *p.p.* to +2.37 *p.p.* per quarter as the volatile food and energy components drop out of the response variable (Section 5.2, Appendix C). A fourth check, reestimating the model with the within-period mean rather than the end-of-quarter value used to aggregate higher-frequency source series, leaves the global–domestic split and the estimated path of the implicit target essentially unchanged (Section

5.2.2, Appendix D).

The policy reading is more nuanced than one based solely on the distance between realized inflation and the target. Large external contributions imply that such a distance is an incomplete scorecard for a small open economy. Observed long-run expectations provide evidence of resilience during the global inflation surge, while the downward drift in the model-implied target shows that alignment with the explicit objective was not complete. The two measures should therefore be monitored jointly. The small footprint of monetary-policy shocks is consistent with much of policy operating through systematic responses, although the decomposition does not by itself establish the effectiveness of those responses. For communication, reporting the implicit target alongside the explicit objective and observed expectations would make both the resilience and the drift of the perceived nominal anchor transparent across episodes (Section 4.8).

We close by acknowledging the scope and limitations of the analysis. The individual methods here are standard, and the finding that a small, very open economy imports much of its inflation volatility is unlikely, by itself, to be surprising. What we consider novel and useful is the evaluative frame: identifying the implicit target as the max-FEV factor of long-run expectations, comparing it directly with the announced objective, and showing both its relative stability and its downward drift through an extreme inflation cycle. This provides a complementary perspective to the distance between realized inflation and the target. The natural next steps are to test the robustness of the implicit-target result to the identification of the implicit-target shock, to use the identified model for optimal-policy counterfactuals that quantify the output-gap and interest-rate paths required to steer inflation to alternative targets (a 2% versus 3% target), and to compare Costa Rica's experience with that of other small open economies over the same global cycle.

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# Online Appendix (Not for publication)

# A Identification algorithm: a computational guide

This appendix restates the identification of Section 3.2 as an explicit, reproducible algorithm. Section 3.2 describes the scheme in words and Table 2 lists the restrictions; here we give the operational recipe actually run in the code. The presentation is deliberately mechanical: it spells out (i) how each of the ten structural shocks is a column of the orthogonal factor $Q$; (ii) how block exogeneity, mutual orthogonality, and contemporaneous exclusions all reduce to *linear* constraints that confine a shock to a subspace; (iii) how a single structural direction is *parametrized as one unit vector drawn uniformly from that subspace* (Algorithm A.1), which is the sole source of randomness in the rotation; (iv) the deterministic max-FEV step that pins down the implicit-target shock; and (v) the sequential construction and the outer accept/reject loop (Algorithms A.2–A.3).

## A.1 Setup and notation

Fix one reduced-form posterior draw $(B, \Sigma)$ from the Gibbs sampler of Section 3.1, where $B$ collects the intercept and the $p$ autoregressive coefficient matrices and $\Sigma$ is the $n \times n$ innovation covariance ($n = 10$). Let

$$L = \mathrm{chol}(\Sigma), \qquad LL' = \Sigma, \tag{3}$$

be the lower-triangular Cholesky factor. Any admissible impact matrix is $A_0^{-1} = L\,Q$ with $Q$ orthogonal ($Q'Q = I_n$), and the reduced-form and structural innovations satisfy $u_t = A_0^{-1}\varepsilon_t$, $\mathbb{E}[\varepsilon_t\varepsilon_t'] = I_n$. Write $q_i$ for the $i$-th column of $Q$: it is a unit vector in $\mathbb{R}^n$ and *is* the $i$-th structural shock, whose vector of contemporaneous impact responses is $Lq_i$. For a variable indexed by the canonical basis vector $e_v$, the impact of shock $q$ on $v$ is the scalar $e_v'Lq = L_{v\cdot}\,q$, where $L_{v\cdot}$ is row $v$ of $L$.

Dynamic responses use the companion form. Let $F$ be the companion matrix of $B$, $J = [\,I_n \;\; 0\,]$ the selection matrix that reads the top $n$ rows, and $G = [\,I_n;\, 0\,]$ its transpose-shaped injector. The matrix of responses of all variables to all structural shocks at horizon $h$ is

$$\Psi_h \;=\; J\,F^{\,h}\,G\,L, \qquad h = 0, 1, \ldots, H, \qquad \Psi_0 = L, \tag{4}$$

so the response of the variables to a structural direction $q$ at horizon $h$ is $\Psi_h\,q$. We use $H = 24$ quarters. Restriction-evaluation horizons are $h = 0, 1, \ldots, H_R$ with $H_R = 4$.[5] Throughout, null$(M)$ denotes an orthonormal basis (stacked as columns) for the null space of $M$, i.e. the orthogonal complement of $M$'s row space.

## A.2 Restrictions as subspaces

Every shock direction $q$ is obtained by (a) confining it to a linear subspace $\mathcal{S} \subseteq \mathbb{R}^n$ that encodes the "hard" restrictions, then (b) drawing a unit vector inside $\mathcal{S}$ and checking the "soft" (sign) restrictions by rejection. Three kinds of hard restriction all take the same linear form:

1. **Orthogonality.** To keep $Q$ orthonormal, each new shock must be orthogonal to all previously fixed columns: $q \in \mathrm{null}(Q'_{\mathrm{fixed}})$, where $Q_{\mathrm{fixed}}$ stacks the columns already placed. This is what makes the admissible space shrink by one dimension each time a shock is pinned down.

[5] The baseline evaluates the sign, zero, and block-exogeneity restrictions over the first four quarters after impact; `RestrictionHorizon` in the code.

2. **Contemporaneous exclusion (zero) restrictions.** "Shock $q$ has zero impact on variable $v$" is $L_{v\cdot}\, q = 0$, i.e. $q \perp L' e_v$. Three such restrictions appear: the exchange-rate shock has no contemporaneous policy-rate response ($q \perp L' e_{\texttt{tpm}}$); the oil-supply shock has no contemporaneous effect on domestic inflation or on non-fuel commodity prices ($q \perp L' e_{\texttt{infCR}}$ and $q \perp L' e_{\texttt{pMSC}}$);[6] and the oil-demand shock has no contemporaneous effect on domestic inflation ($q \perp L' e_{\texttt{infCR}}$).
3. **Block exogeneity (dynamic, over $h \leq H_R$).** The five domestic shocks must not move the five-variable global block, contemporaneously or at any horizon up to $H_R$. Let $\mathcal{G} = \{\texttt{pComb}, \texttt{pMSC}, \texttt{gapUS}, \texttt{infSC}, \texttt{iUS}\}$ index the global rows. Stack those rows of the response matrices (4) across horizons,

$$R_{\text{ext}} \;=\; \begin{bmatrix} \Psi_0[\mathcal{G}, :] \\ \Psi_1[\mathcal{G}, :] \\ \vdots \\ \Psi_{H_R}[\mathcal{G}, :] \end{bmatrix} \in \mathbb{R}^{5(H_R+1)\times n}, \qquad N \;=\; \text{null}(R_{\text{ext}}), \tag{5}$$

and let $N \in \mathbb{R}^{n\times 5}$ be an orthonormal basis for the resulting five-dimensional *domestic shock space*. Every domestic shock lives in $\text{col}(N)$; if $\dim \text{col}(N) < 5$ the draw is discarded.

**Coordinate reduction for the domestic block.** Because the five domestic shocks all lie in $\text{col}(N)$, we parametrize a domestic direction as $q = Na$ with $a \in \mathbb{R}^5$, $\|a\| = 1$. Orthogonality and exclusion constraints then become linear constraints on the *five-vector* $a$: orthogonality $q_i \perp q_j$ is $a_i \perp a_j$ (since $N'N = I_5$), and a zero-impact restriction $L_{v\cdot} q = 0$ becomes $a \perp (N' L' e_v)$. The domestic block is therefore identified entirely inside a five-dimensional space, and each domestic shock is a unit vector drawn from a subspace of $\mathbb{R}^5$ whose dimension falls from 4 (after the deterministic implicit-target direction is removed) down to 1. The five global shocks are constructed directly in $\mathbb{R}^n$, in the orthogonal complement of the five already-placed domestic columns.

### A.3 Parametrizing a structural direction as a single unit vector

The one non-deterministic operation in the whole scheme is drawing a unit vector uniformly from a subspace. Given an orthonormal basis $B \in \mathbb{R}^{m\times d}$ for a $d$-dimensional subspace, Algorithm A.1 returns a random unit vector in $\text{col}(B)$.

**Algorithm A.1** DrawUnitVector($B$) — uniform draw on the sphere of a subspace

**Require:** orthonormal basis $B \in \mathbb{R}^{m\times d}$ (columns), $d \geq 1$

**if** $d = 1$ **then**
  **return** $B$ ▷ one-dimensional: direction is deterministic
**else**
  draw $z \sim \mathcal{N}(0, I_d)$ ▷ isotropic Gaussian in the reduced coordinates
  $v \leftarrow B\,(z/\|z\|)$ ▷ map to $\mathbb{R}^m$; $\|v\| = 1$ since $B$ is orthonormal
  **return** $v$
**end if**

[6] The oil-supply exclusion on non-fuel commodity prices (pMSC) is imposed in the code but not displayed in Table 2; it separates an oil-*supply* disturbance, which leaves the broad non-fuel commodity basket unmoved on impact, from an oil-*demand* disturbance, which raises it. The zero on domestic inflation is the impact side of the $h$=1 "$+^{h1}$" restriction: fuel-price pass-through into the regulated domestic price index is delayed by one quarter.

Because $z$ is isotropic, $z/\|z\|$ is uniform on the unit sphere $S^{d-1}$, and left-multiplication by the orthonormal $B$ is an isometry onto $\mathrm{col}(B)$; hence $v$ is uniform (rotationally invariant, i.e. Haar) on the unit sphere of the subspace. This is exactly the sense in which the identification "randomly rotates" within the admissible space: every candidate rotation $Q$ is a deterministic function of the reduced-form draw $(B, \Sigma)$ and of the Gaussian vectors $z$ consumed by the successive DrawUnitVector calls. When $d = 1$ the subspace is a line and the direction is forced (only its sign is free), so no randomness is used—this is how the domestic-supply and global-supply shocks, and the deterministic implicit-target direction, are handled.

**Sign normalization.** A drawn direction $q$ and its antipode $-q$ are the same shock up to a relabeling of sign. We fix the sign so that a designated variable $v$ responds with a chosen sign $\sigma \in \{+1, -1\}$:

$$\textsc{Orient}(q; v, \sigma) \; = \; \begin{cases} q, & \sigma\,(L_v.q) \geq 0, \\ -q, & \text{otherwise.} \end{cases} \tag{6}$$

This is a normalization, not an identifying restriction; it selects one of the two antipodal points on the sphere.

### A.4 The implicit-target direction (max-FEV)

The implicit-target shock is the only domestic direction that is *deterministic* given $(B, \Sigma)$. Working in the reduced coordinates $a \in \mathbb{R}^5$ of the domestic space (so $q = Na$), define the symmetric positive-semidefinite matrix that accumulates the squared response of long-run inflation expectations ($e_{\texttt{expInf60}}$) over the horizon:

$$M \; = \; \sum_{h=0}^{H} \big(N'\Psi_h'\, e_{\texttt{expInf60}}\big)\big(N'\Psi_h'\, e_{\texttt{expInf60}}\big)' \; = \; N'\left[\sum_{h=0}^{H} \Psi_h'\, e_{\texttt{expInf60}}\, e_{\texttt{expInf60}}'\, \Psi_h\right]N \; \in \; \mathbb{R}^{5\times 5}. \tag{7}$$

The implicit-target coordinate $a^\star$ is the leading eigenvector of $(M+M')/2$; it maximizes $\sum_h \big(e_{\texttt{expInf60}}'\Psi_h N a\big)^2$ over unit $a$, i.e. the domestic direction whose responses account for the largest accumulated (squared) movement—equivalently the largest share of the forecast-error variance—of long-run expectations. The structural direction is $q_{\mathrm{MI}} = \textsc{Orient}(Na^\star; \texttt{expInf60}, +1)$. Because it solves an eigenvalue problem rather than being drawn, $q_{\mathrm{MI}}$ is identical across every candidate rotation for a given reduced-form draw.

### A.5 Sequential construction of one rotation

Algorithm A.2 assembles the ten columns of $Q$ in a fixed order. The domestic block is built first, inside $\mathrm{col}(N)$; the global block follows, in the orthogonal complement of the placed columns. Sign restrictions are checked on the impact vector $Lq$ (and, for the oil shocks, on the horizon-one vector $\Psi_1 q$); a shock that is drawn (not forced) is re-drawn up to $R_{\max} = 100$ times before the candidate is abandoned.

**Algorithm A.2** $\textsc{IdentifyOneRotation}(L, \{\Psi_h\}, N)$ — one candidate $Q$

$Q \leftarrow 0_{n\times n}$

*– Domestic block, in the coordinates of $N$ –*

**Implicit target:** $q_{\mathrm{MI}} \leftarrow$ max-FEV direction (7); place $Q[:, \texttt{expInf60}] \leftarrow q_{\mathrm{MI}}$

**Monetary policy:** draw $a$ from $\mathrm{null}(a'_{\mathrm{MI}})$; $s \leftarrow \textsc{Orient}(Na; \texttt{tpm}, +)$;
accept iff $L_{\texttt{tcn}\cdot}s < 0$, $L_{\texttt{infCR}\cdot}s < 0$, $L_{\texttt{gapCR}\cdot}s < 0$; place $Q[:, \texttt{tpm}] \leftarrow s$

**Exchange rate:** draw $a$ from $\mathrm{null}([\, N'L'e_{\texttt{tpm}},\ a_{\mathrm{MI}},\ a_{\mathrm{PM}}\,]')$; $s \leftarrow \textsc{Orient}(Na; \texttt{tcn}, +)$;
accept iff $L_{\texttt{infCR}\cdot}s > 0$; place $Q[:, \texttt{tcn}] \leftarrow s$ ▷ zero contemp. `tpm` response

**Domestic demand:** draw $a$ from $\mathrm{null}([\, a_{\mathrm{TCN}}, a_{\mathrm{MI}}, a_{\mathrm{PM}}\,]')$; $s \leftarrow \textsc{Orient}(Na; \texttt{gapCR}, +)$;
accept iff $L_{\texttt{infCR}\cdot}s > 0$; place $Q[:, \texttt{gapCR}] \leftarrow s$

**Domestic supply:** $a \leftarrow$ the remaining 1-D direction $\mathrm{null}([\, a_{\mathrm{PIB}}, a_{\mathrm{TCN}}, a_{\mathrm{PM}}, a_{\mathrm{MI}}\,]')$; $s \leftarrow \textsc{Orient}(Na; \texttt{infCR}, +)$;
accept iff $L_{\texttt{gapCR}\cdot}s < 0$ (sign check only); place $Q[:, \texttt{infCR}] \leftarrow s$

*– Global block, in* $\mathrm{null}(Q')$ *of the placed columns –*

**U.S. monetary policy:** draw $s$ from $\mathrm{null}(Q')$; $s \leftarrow \textsc{Orient}(s; \texttt{iUS}, +)$;
accept iff $L_{\texttt{gapUS}\cdot}s < 0$, $L_{\texttt{infSC}\cdot}s < 0$; place $Q[:, \texttt{iUS}] \leftarrow s$

**Oil supply:** draw $s$ from $\mathrm{null}([\, L'e_{\texttt{infCR}},\ L'e_{\texttt{pMSC}},\ Q\,]')$; $s \leftarrow \textsc{Orient}(s; \texttt{pComb}, +)$;
accept iff $(\Psi_1 s)_{\texttt{infCR}} > 0$ and $L_{\texttt{gapUS}\cdot}s < 0$; place $Q[:, \texttt{pComb}] \leftarrow s$

**Oil demand:** draw $s$ from $\mathrm{null}([\, L'e_{\texttt{infCR}},\ Q\,]')$; $s \leftarrow \textsc{Orient}(s; \texttt{pComb}, +)$;
accept iff $(\Psi_1 s)_{\texttt{infCR}} > 0$, $L_{\texttt{pMSC}\cdot}s > 0$, $L_{\texttt{gapUS}\cdot}s > 0$; place $Q[:, \texttt{gapUS}] \leftarrow s$

**Global demand:** draw $s$ from $\mathrm{null}(Q')$; $s \leftarrow \textsc{Orient}(s; \texttt{pMSC}, +)$;
accept iff $L_{\texttt{gapUS}\cdot}s > 0$, $L_{\texttt{infSC}\cdot}s > 0$, $L_{\texttt{infCR}\cdot}s > 0$; place $Q[:, \texttt{pMSC}] \leftarrow s$

**Global supply:** $s \leftarrow$ the remaining 1-D direction $\mathrm{null}(Q')$; $s \leftarrow \textsc{Orient}(s; \texttt{infSC}, +)$;
accept iff $L_{\texttt{gapUS}\cdot}s < 0$ and $L_{\texttt{infCR}\cdot}s > 0$ (sign check only); place $Q[:, \texttt{infSC}] \leftarrow s$

**return** $Q$ if every step succeeded and $\|Q'Q - I_n\|_F < 10^{-6}$; otherwise report failure

In lines that "draw $a$" or "draw $s$", the vector is obtained by $\textsc{DrawUnitVector}$ on the indicated orthonormal null-space basis and, for the sign-restricted shocks, redrawn up to $R_{\max} = 100$ times until the accept condition holds. Here $a_{\mathrm{MI}}, a_{\mathrm{PM}}, a_{\mathrm{TCN}}, a_{\mathrm{PIB}}$ denote the coordinate representations (in $N$) of the already-placed domestic directions used to build the successive null spaces. The two "remaining 1-D direction" steps consume no randomness: once every other shock in the block is fixed, the last direction is determined up to sign, so only its sign restriction is checked.

## A.6 Outer accept/reject loop

Algorithm A.3 wraps the rotation search inside the loop over reduced-form draws.

**Algorithm A.3** IdentifySVAR — outer loop over posterior draws

**Require:** reduced-form draws $\{(B^{(d)}, \Sigma^{(d)})\}_{d=1}^{D}$; targets $N_{\text{acc}} = 10{,}000$, $C_{\max} = 500$

accepted $\leftarrow 0$
**for** $d = 1, 2, \ldots, D$ **do**
  form $L, F, \{\Psi_h\}_{h=0}^{H}$ and $N = \text{null}(R_{\text{ext}})$ from $(B^{(d)}, \Sigma^{(d)})$ ▷ Eqs. (3)–(5)
  **if** $\dim \text{col}(N) < 5$ **then continue** ▷ domestic space too small
  **end if**
  **for** $c = 1, 2, \ldots, C_{\max}$ **do** ▷ candidate rotations for this draw
    $Q \leftarrow$ IdentifyOneRotation$(L, \{\Psi_h\}, N)$ ▷ Algorithm A.2
    **if** $Q$ succeeded **then**
      store $Q$, impact $A_0^{-1} = LQ$, shocks $\varepsilon = U(A_0^{-1})^{-\top}$, and IRFs; accepted += 1
      **break** ▷ keep the first admissible rotation
    **end if**
  **end for**
  **if** accepted $\geq N_{\text{acc}}$ **then break**
  **end if**
**end for**

The baseline retains $N_{\text{acc}} = 10{,}000$ accepted structural draws, with an acceptance rate of 67.8% over reduced-form draws (Section 3.2). Each accepted draw contributes one $Q$—and hence one impact matrix $A_0^{-1} = LQ$, one set of structural shocks, and one set of impulse responses—to the posterior over structural objects from which all reported medians and bands are computed. Two features are worth emphasizing for anyone reproducing the scheme. First, the map from randomness to structure is transparent: fixing the reduced-form draw and the Gaussian vectors consumed by DrawUnitVector reproduces $Q$ exactly, and the implicit-target column never depends on any of those draws. Second, the ordering of the shocks in Algorithm A.2 carries no recursive (Cholesky-style) causal content: the *identified set*—the collection of rotations satisfying all the exclusion, block-exogeneity, and sign restrictions—is a fixed object, independent of the order in which the free directions are drawn, and the two forced (one-dimensional) directions simply absorb whatever remains. The draw order does, however, shape the *sampling density over* that set: because each free direction is drawn uniformly from the current subspace and, in the presence of the zero (exclusion) restrictions, no importance-reweighting is applied, the construction induces a particular, order-dependent prior over admissible rotations rather than the conditionally-uniform prior of Arias et al. (2018). We treat this as an implicit prior choice and verify, in Section 3.2, that its consequences for the reported decomposition are minor: permuting the draw order of the freely-rotated shocks leaves the global–domestic split and the implicit-target and monetary-policy conclusions essentially unchanged, moving mainly individual, mutually correlated shocks within each block at the finest ten-way disaggregation.

## A.7 Robustness to the draw order

Table A.1 reports the draw-order check discussed in Section 3.2. We re-identify the model under six orderings of the freely rotated shocks, consisting of the baseline, three systematic reversals, and two shuffles. Each ordering reuses a single reduced-form posterior and 10,000 accepted structural draws. The table reports posterior-mean baseline contributions and the largest variation across orderings. The global–domestic split (Lens 1) is essentially invariant, while the finer supply–demand and individual-shock decompositions exhibit some within-block reallocation without changing the sign or ranking of the dominant contributions. The permutable set is constrained by the exclusion restrictions: because the oil-supply shock carries two contemporaneous zeros, it cannot be drawn as the last free shock in the global block, and the implicit-target direction (drawn first) and the two residual supply shocks are fixed by construction.

Table A.1: Posterior-mean sensitivity of the historical decomposition to the draw order

| **Object** | **Window** | **Baseline mean** | **Across orderings** |
|---|---|---|---|
| Global factors | Full IT period | $-0.37\,p.p.$ | Maximum change below $0.01\,p.p.$ |
| Domestic factors | Full IT period | $-0.61\,p.p.$ | Maximum change below $0.01\,p.p.$ |
| Global factors | Inflation surge | $+5.17\,p.p.$ | Maximum change below $0.01\,p.p.$ |
| Domestic factors | Inflation surge | $-0.85\,p.p.$ | Maximum change below $0.01\,p.p.$ |
| Implicit-target contribution | All five windows | | Maximum change about $0.002\,p.p.$ |
| Domestic monetary policy | Inflation surge | $+0.25\,p.p.$ | Range: $+0.06$ to $+0.25\,p.p.$ |
| Individual global shocks | Inflation surge | | Maximum reallocation about $0.28\,p.p.$ |
| Supply–demand lens | Inflation surge | | Maximum reallocation about $0.35\,p.p.$ |

**Notes:** Contributions are posterior means, averaged over the indicated window. "Maximum change" is the largest absolute change from the baseline ordering. "Maximum reallocation" summarizes changes among components that leave the broader block approximately unchanged. All orderings reuse one reduced-form posterior with 10,000 accepted structural draws.

# B Forecast-error variance decompositions

The historical decomposition in Section 4 attributes the *realized sample path* of each variable to the shocks that actually hit the economy. A complementary object is the *forecast-error variance decomposition* (FEVD): for a given horizon $h$, the share of the variance of the $h$-step-ahead forecast error of a variable that is attributable to each structural shock, independent of which shocks happened to be large or small over the historical sample. We report FEVDs computed from the same accepted structural draws underlying the rest of the paper, cumulating squared structural impulse responses over horizons $0, \ldots, h$ and expressing each shock's contribution as a percentage of the total $h$-step-ahead variance; the reported point estimate is the posterior *mean* share (not the median), which is the aggregation that guarantees the shares of the ten shocks sum to exactly 100% at every horizon.

## B.1 FEVD by individual shock

Figures B.1–B.5 report the full ten-shock FEVD for Costa Rican inflation and the other four domestic variables, out to a five-year (20-quarter) horizon.

Figure B.1: FEVD of Costa Rican inflation (`infCR`).

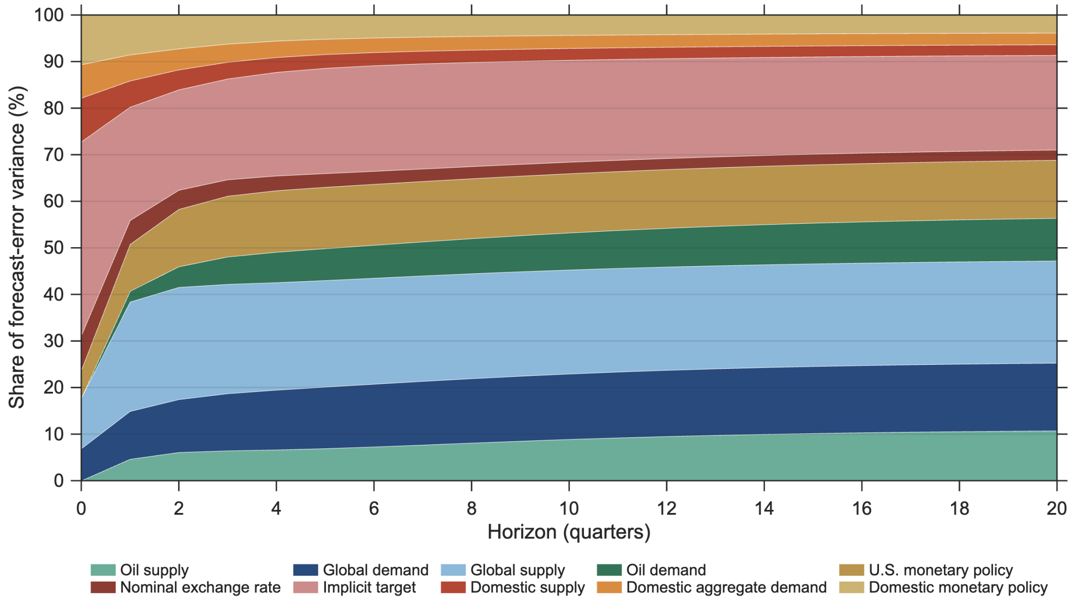



Figure B.2: FEVD of the nominal exchange rate (`tcn`).

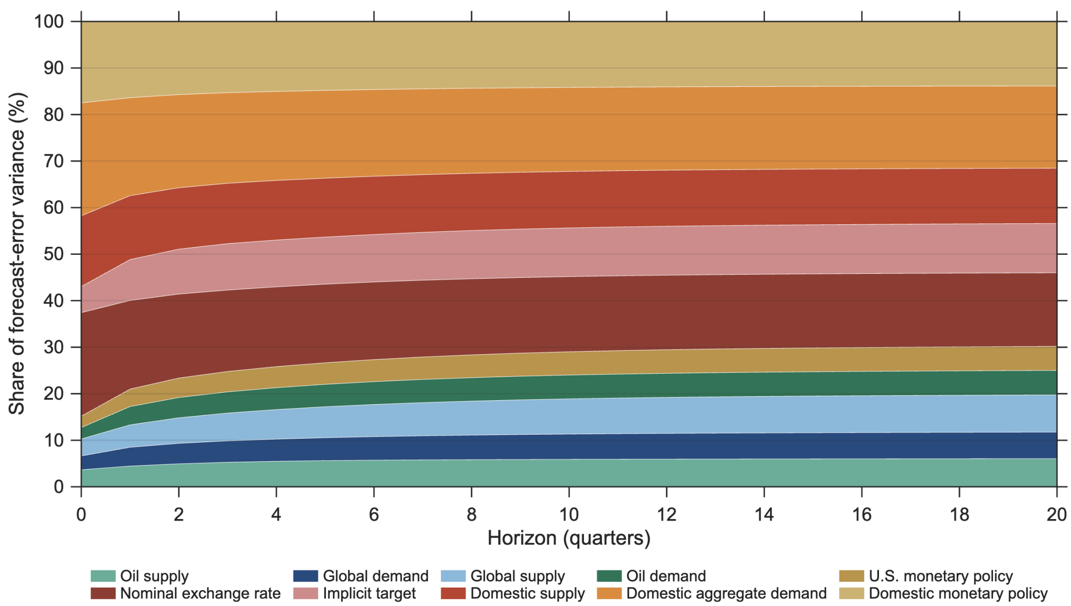


Figure B.3: FEVD of long-run (60-month) inflation expectations (`expInf60`).

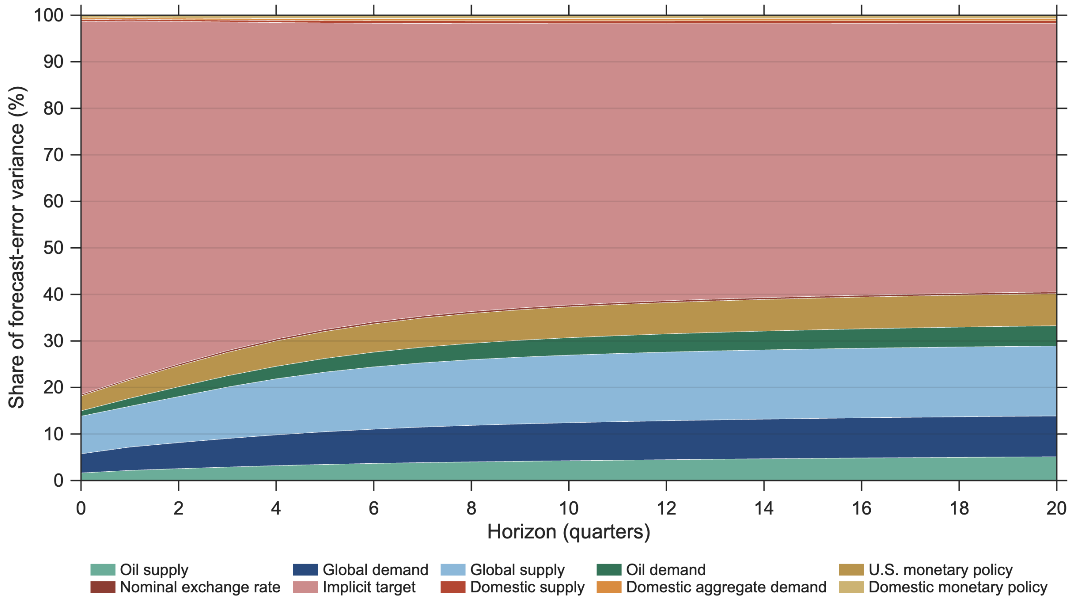



Figure B.4: FEVD of the Costa Rican output gap (`gapCR`).

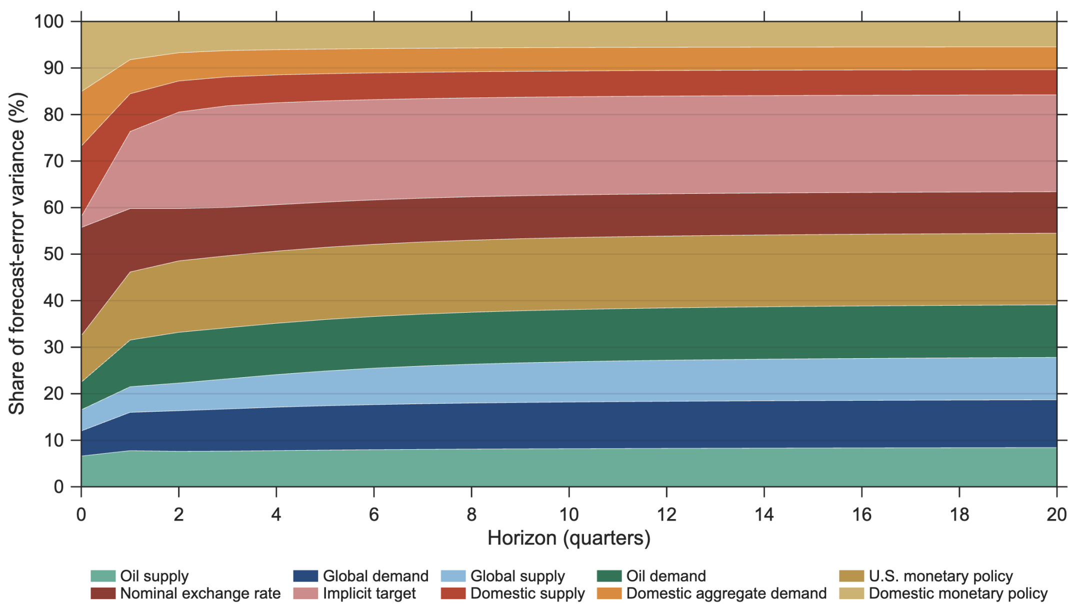
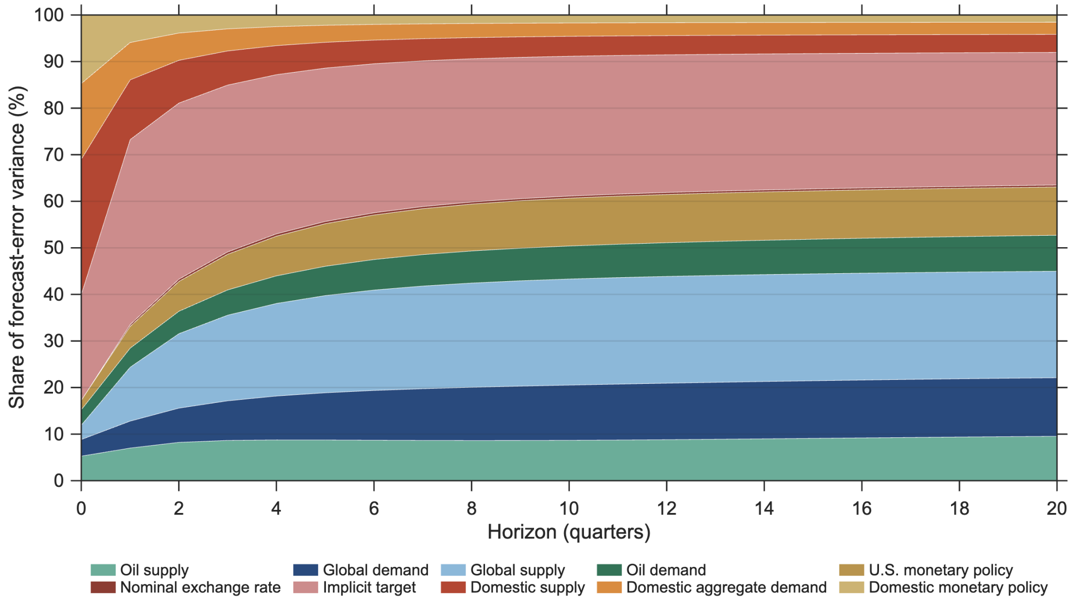


Figure B.5: FEVD of the monetary policy rate (`tpm`).




## B.2 FEVD by aggregated lens

Figures B.6 and B.7 aggregate the same ten-shock FEVD for Costa Rican inflation into the Lens 1 (global vs. domestic) and Lens 2 (supply vs. demand) groupings used in Table 4, obtained by summing shock shares within each group (exact within a draw, since the shares of a partition always sum to 100%). The global block already accounts for roughly 24% of the variance of the inflation forecast error on impact, rising to about 69% at the five-year horizon—the same global dominance documented for the realized sample path in Section 4, now shown to hold unconditionally on which shocks happened to be large historically.

Figure B.6: FEVD of Costa Rican inflation, aggregated into global vs. domestic factors (Lens 1).

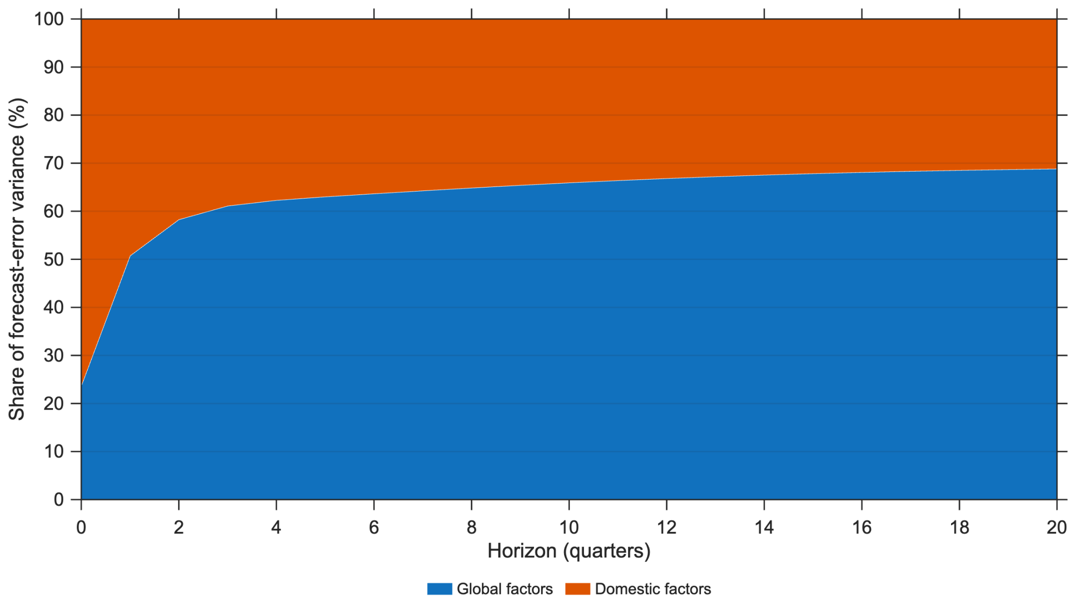
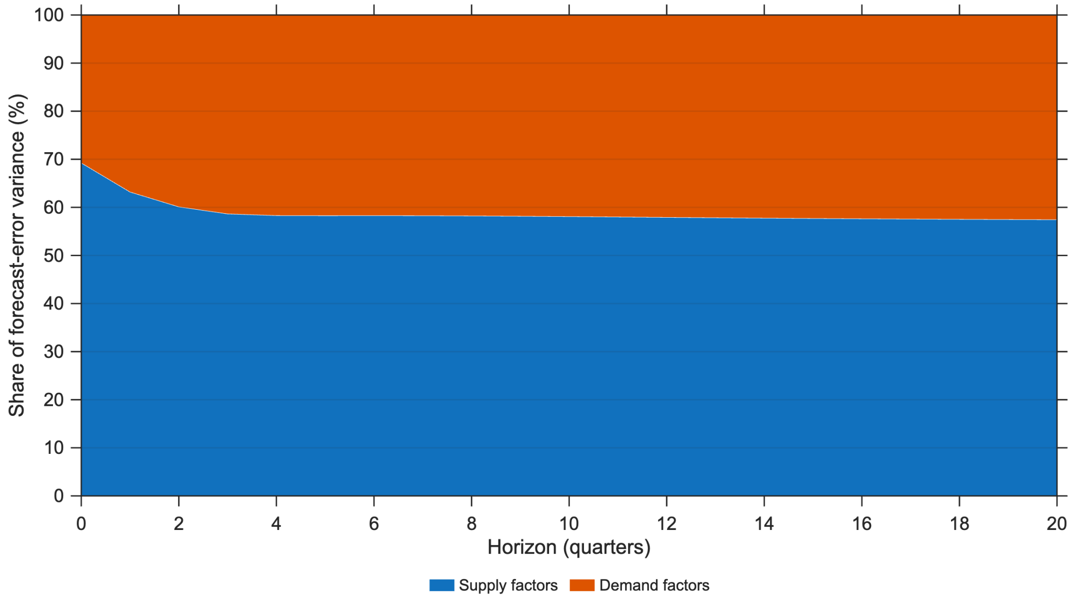


Figure B.7: FEVD of Costa Rican inflation, aggregated into supply vs. demand factors (Lens 2).




# C Robustness: core inflation (IEF)

This appendix reports the robustness check summarized in Section 5.2: the full ten-variable model, reestimated with the BCCR's IEF core-inflation indicator in the `infCR` slot instead of headline CPI inflation, holding every other variable, restriction, and hyperparameter fixed. Table C.1 reports a focused comparison of the principal mean contributions; Figures C.8–C.11 reproduce the four figures most central to the paper's argument (the full ten-shock decomposition, the global/domestic lens, the implicit target, and the global/domestic FEVD) using core inflation as the response variable.

Table C.1: Selected posterior-mean contributions during the inflation surge (p.p.)

| **Contribution** | **Core inflation** | **Headline inflation** |
|---|---:|---:|
| Global factors | +2.37 | +5.17 |
| Domestic monetary policy | +0.16 | +0.25 |

**Notes:** Posterior-mean cumulative contributions to the deviation of inflation from its model-implied baseline, averaged over 2021Q4–2023Q1. The specifications differ only in the inflation measure.

Figure C.8: Core inflation (IEF): historical decomposition into all ten structural shocks, 2018–2026.

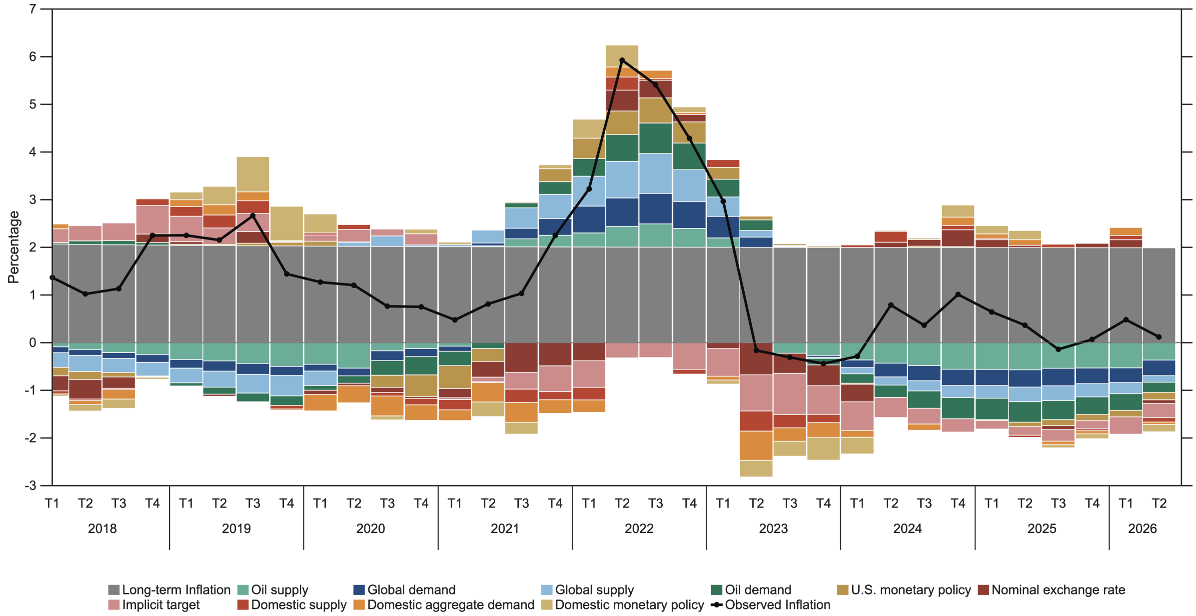



Figure C.9: Core inflation (IEF): historical decomposition, global vs. domestic factors, 2018–2026.

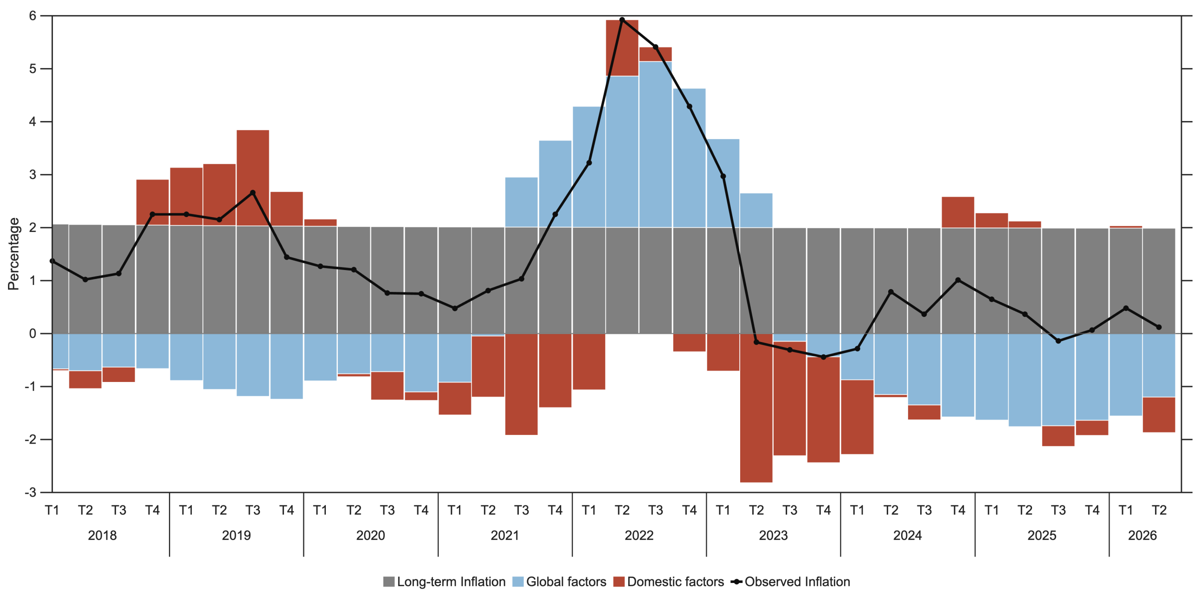
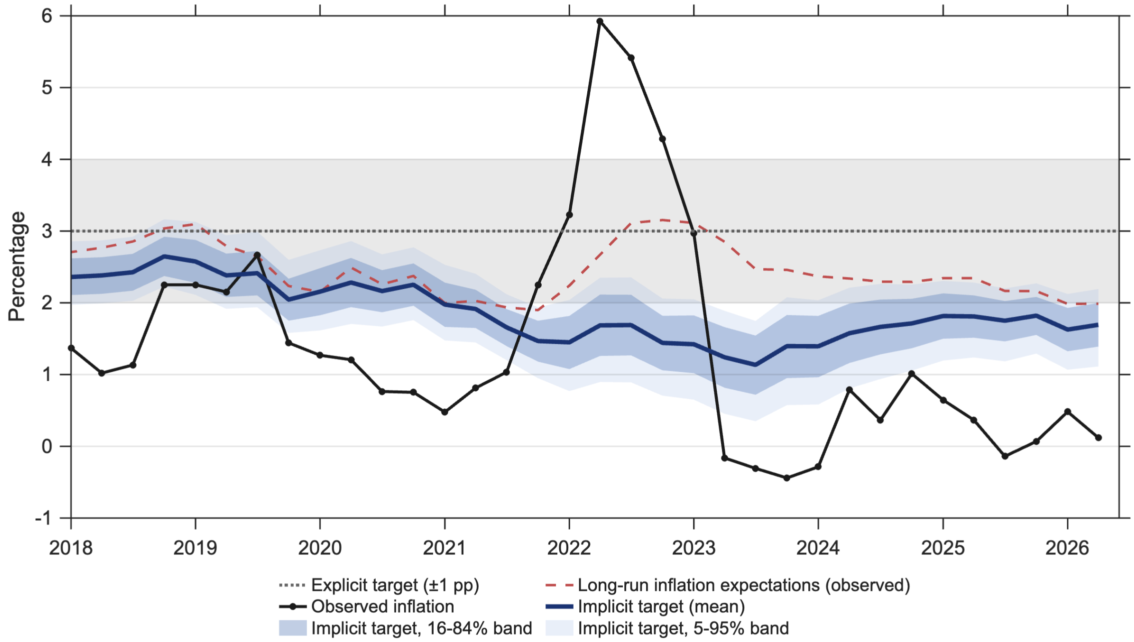
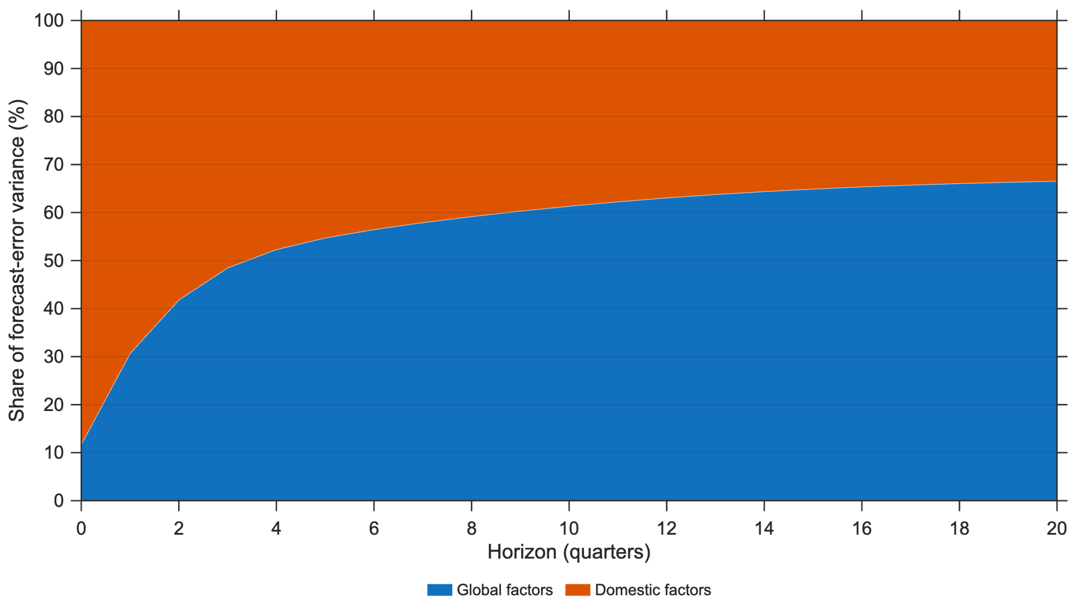


Figure C.10: Core inflation (IEF): the implicit target versus the explicit target.




**Notes:** Same construction as Figure 7, with core inflation in place of headline CPI throughout.

Figure C.11: Core inflation (IEF): FEVD aggregated into global vs. domestic factors (Lens 1).




# D Robustness: within-period mean aggregation

This appendix reports the robustness check summarized in Section 5.2.2: the full ten-variable model, reestimated with every higher-frequency source series aggregated to the model's quarterly frequency using the within-period *mean* rather than the baseline end-of-quarter (last) value, holding every variable, restriction, and hyperparameter fixed. Figures D.12–D.15 reproduce the figures most central to the paper's argument—the impulse responses of inflation, the full ten-shock decomposition, the global/domestic lens, and the implicit target—using this alternative aggregation convention. As Section 5.2.2 reports, the headline global–domestic split and the implicit target are essentially unaffected by this choice.

Figure D.12: Within-period mean aggregation: impulse responses of headline inflation.

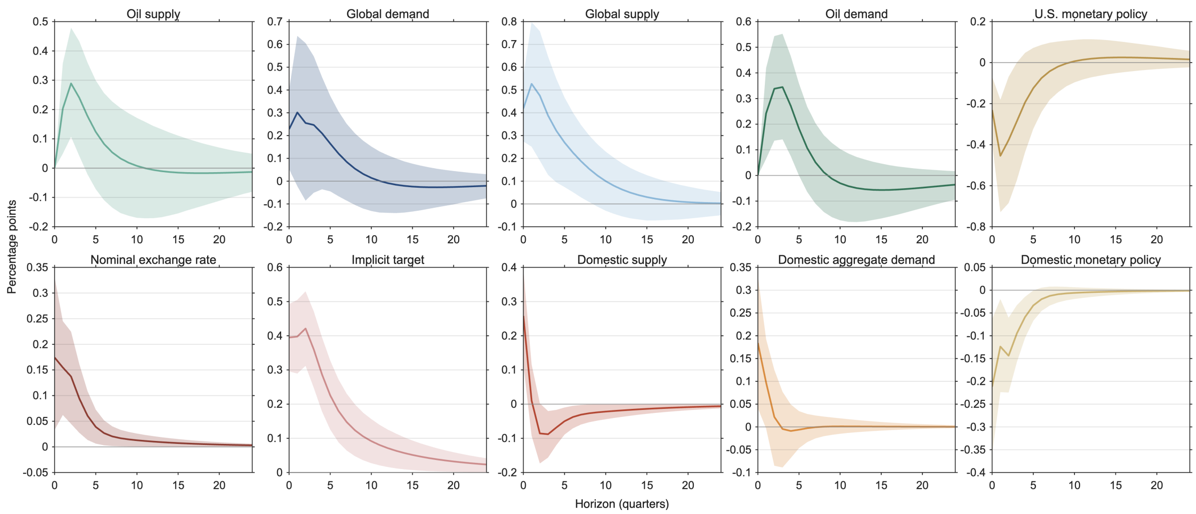



Figure D.13: Within-period mean aggregation: historical decomposition into all ten structural shocks, 2018–2026.

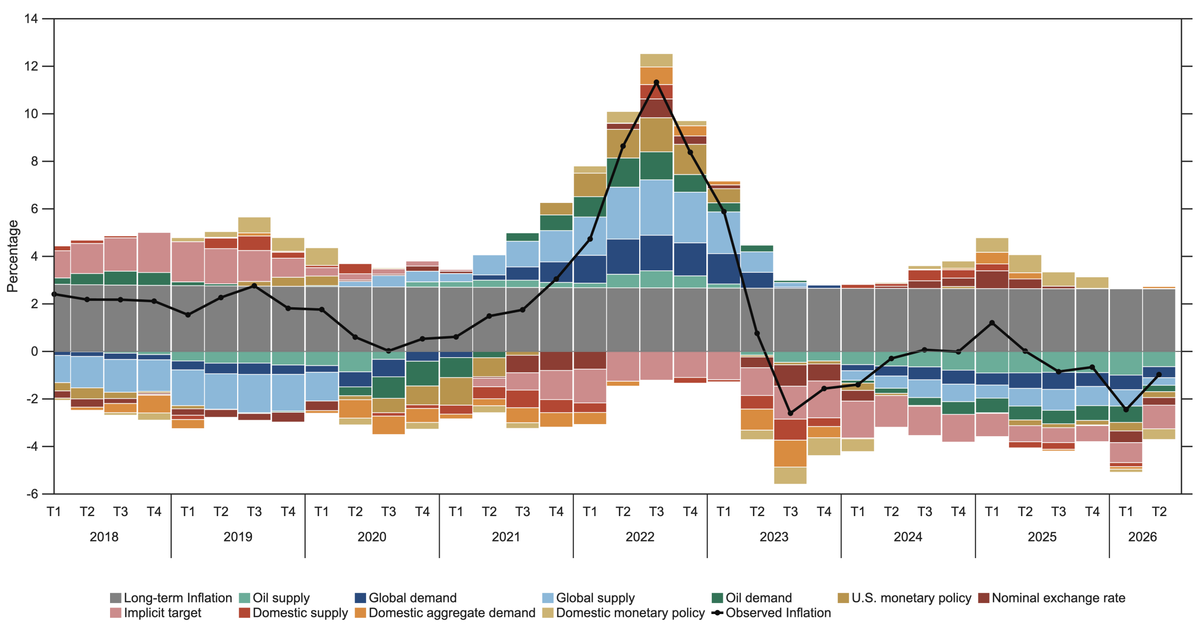


Figure D.14: Within-period mean aggregation: historical decomposition, global vs. domestic factors, 2018–2026.

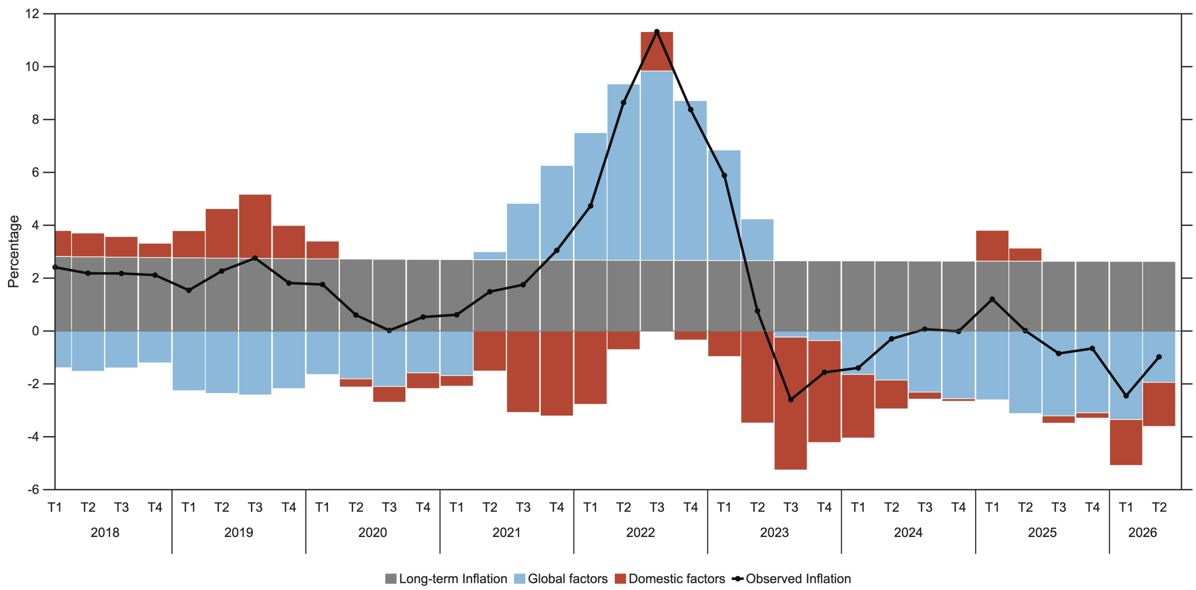
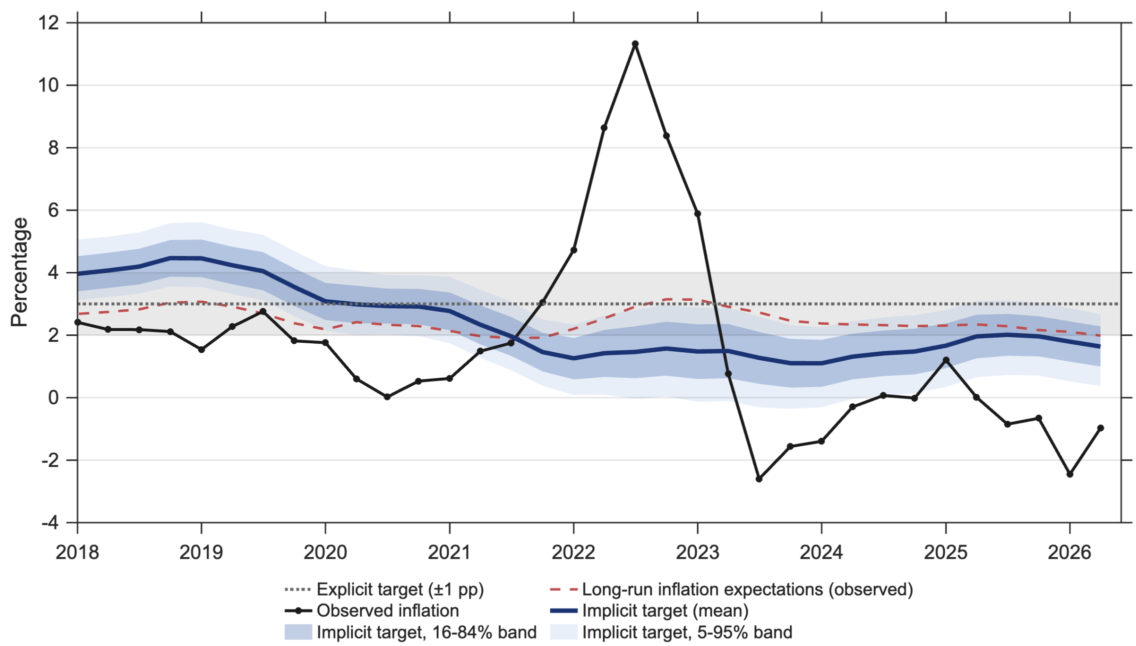



Figure D.15: Within-period mean aggregation: the implicit target versus the explicit target.




**Notes:** Same construction as Figure 7, with all higher-frequency source series aggregated to quarterly frequency using the within-period mean instead of the end-of-quarter value.

# E Data: sources, construction, and transformations

This appendix documents, series by series, how each of the ten model variables is built from its raw source, the frequency at which it is observed, the transformation applied, and how the ten series are aligned into the estimation sample. It complements the summary in Section 2 and Table 1. All construction is carried out in the routine `PrepareData.m`; the model matrix is assembled by `CreateVAR.m`.

We do not impose an explicit cointegrating structure because the BVAR is estimated in levels, allowing long-run relationships to be represented without fixing their number or form in advance, while Bayesian shrinkage regularizes estimation without requiring preliminary unit-root and cointegration-rank tests.

## E.1 The construction pipeline

Each series is first built at its *native* frequency (daily, monthly, or quarterly), with its own source-specific cleaning and transformation, and stored as a dated time series. The estimation matrix is then assembled in three steps. (i) A common model frequency is chosen as the *lowest* frequency among the selected variables; because the U.S. output gap is quarterly, the ten-variable model is estimated at *quarterly* frequency. (ii) Every higher-frequency series is aggregated to quarterly by the last-value-in-period (end-of-quarter) convention in the baseline, with a within-quarter mean available as a robustness alternative. (iii) The aggregated series are synchronized on the intersection of their dates and rows with any missing value are dropped, yielding the longest common non-missing span, 2009Q1–2026Q2 ($T = 70$ quarterly observations). Sources labelled "Producto Interno" and "Indicadores Económicos" below are, respectively, internal Banco Central de Costa Rica (BCCR) products and series from the BCCR's public economic-indicators portal; "FRED" is the Federal Reserve Bank of St. Louis database.

Table E.1: Raw sources, native frequency, and transformations

| Code | Provider | Source file / sheet / column | Native | Transformation |
|---|---|---|---|---|
| ***Global block*** | | | | |
| `pComb` | Producto Interno | `MatPrimInt.xlsx`, sheet *DAAE (mensual)*, col. *Combustibles* | Monthly | Monthly % change, $100(x_t/x_{t-1} - 1)$ |
| `pMatSinComb` | Producto Interno | `MatPrimInt.xlsx`, sheet *DAAE (mensual)*, col. *Total sin combustible* | Monthly | Monthly % change, $100(x_t/x_{t-1} - 1)$ |
| `gapUS` | FRED | `GDPC1.csv` (real GDP, chained, SA) | Quarterly | $100(\log x_t - \tau_t)$, HP trend $\tau_t$, $\lambda = 1600$ |
| `infSC` | Indic. Econ. | `InflSC.xlsx`, sheet *Series* | Monthly | None (year-on-year %) |
| `iUS` | FRED / Atlanta Fed | `EFFR.csv`, spliced with `WuXiaShadowRate.xlsx` at the ZLB | Daily | Aggregated to monthly; ZLB months replaced by Wu–Xia shadow rate |
| ***Domestic block*** | | | | |
| `tcn` | Indic. Econ. | `TCN.xlsx`, sheet *Series*, mean of *compra/venta* | Daily | Aggregated to monthly level, then monthly % change $100(x_t/x_{t-1} - 1)$ |
| `expInf60` | Indic. Econ. | `EXPINFL60.xlsx`, sheet *Series* (60-month expectations) | Monthly | None |
| `infCR` | Indic. Econ. | `IPC_tasa_variacion.xlsx`, sheet *Series* (CPI) | Monthly | None (year-on-year %) |
| `gapCR` | Producto Interno | `PIBreal.xlsx`, sheet *Mensuales*, real chained-volume col. (ref. 2022) | Monthly | X-13ARIMA-SEATS, then $100(\log x_t^{\mathrm{SA}} - \tau_t)$, HP $\lambda = 15{,}917$ |
| `tpm` | Indic. Econ. | `TPM.xlsx`, sheet *Series* | Daily | Aggregated to monthly (level) |

**Aggregation to the model (quarterly) frequency** uses the last-value-in-period convention in the baseline (within-quarter mean as an alternative). Series read from Excel drop rows with missing dates or values; the monthly real-GDP series additionally drops months beyond the current month, since `PIBreal.xlsx` carries BCCR projections through 2031.

Figure E.1 plots the ten series as they enter the model—at the quarterly frequency, after the transformations in Table E.1 and end-of-quarter aggregation—over the estimation sample.

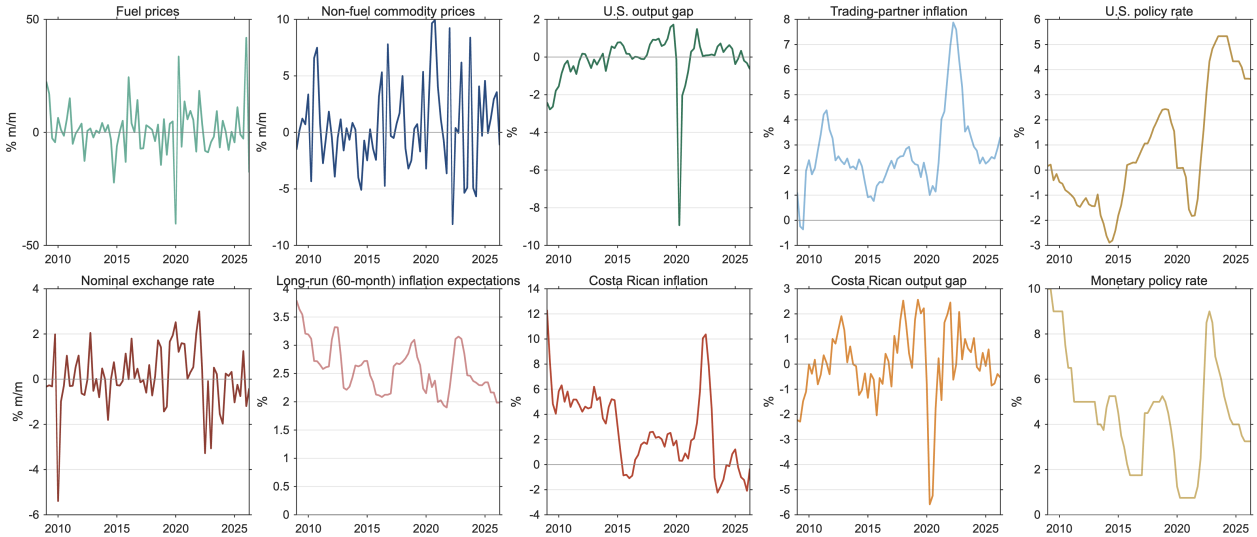



Figure E.1: The ten model variables as they enter the VAR, 2009Q1–2026Q2.

**Notes:** Each panel plots one endogenous variable at the quarterly model frequency over the estimation sample, after the transformation in Table E.1 and last-value-in-period aggregation. Commodity prices and the exchange rate are monthly percentage changes ("% m/m"); the output gaps, inflation rates, expectations, and policy rates are in percent. The Costa Rican output gap (`gapCR`) is shown after X-13ARIMA-SEATS seasonal adjustment (Appendix E.5).

## E.2 Global block

**Fuel and non-fuel commodity prices (`pComb`, `pMatSinComb`).** Both are taken from the BCCR's internal International Raw-Materials Price Index (`MatPrimInt.xlsx`, monthly sheet): the *Combustibles* column for fuels and the *Total sin combustible* column for the non-fuel aggregate. Each enters the model as a monthly percentage change, $100\,(x_t/x_{t-1} - 1)$, so that the two commodity blocks are stationary and measured in comparable growth units.

**U.S. output gap (`gapUS`).** Built from U.S. real GDP (FRED series `GDPC1`, chained 2017 dollars, seasonally adjusted at source and quarterly). We take logs and apply a Hodrick–Prescott filter with the conventional quarterly smoothing constant $\lambda = 1600$; the gap is the percentage deviation from trend, $100\,(\log x_t - \tau_t)$. Because `GDPC1` is already seasonally adjusted, no seasonal adjustment is applied. The output gap is used, rather than a published U.S. gap estimate, because official gaps are released with a longer lag than GDP itself.

**Trading-partner inflation (`infSC`).** The BCCR's Trading-Partner Inflation Index (`InflSC.xlsx`), a consumption-weighted index of year-on-year consumer-price inflation across Costa Rica's main trading partners, enters without transformation (it is already a year-on-year rate).

**U.S. policy rate (`iUS`).** The daily effective federal funds rate (FRED `EFFR`) is aggregated to monthly. To capture the stance of unconventional policy when the nominal rate was constrained, each month in which the Wu–Xia shadow federal funds rate (`WuXiaShadowRate.xlsx`) is negative—the zero-lower-bound period—has its value replaced by that shadow rate. The splice is performed on month-start-aligned dates, so `iUS` equals the effective funds rate outside the ZLB and the Wu–Xia shadow rate within it.

## E.3 Domestic block

**Nominal exchange rate (`tcn`).** The daily colón/US$ reference rates (`TCN.xlsx`) are averaged across the BCCR buy (*compra*) and sell (*venta*) quotes, aggregated to a monthly level, and entered as a monthly percentage change, $100\,(x_t/x_{t-1} - 1)$. A log-level alternative, $100 \log x_t$, is also constructed in the code (variable `tipoCambioNominalLogNivel`) and can replace the percentage-change series; both carry the model code `tcn`, so only one is used in a given specification.

**Long-run inflation expectations (`expInf60`).** The BCCR survey of 60-month-ahead inflation expectations (`EXPINFL60.xlsx`) enters in levels, without transformation. This is the series whose forecast-error variance the implicit-target shock is defined to maximize (Section 3.2).

**Headline inflation (`infCR`).** Year-on-year growth of the consumer price index (`IPC_tasa_variacion.xlsx`), entered without transformation. As a robustness alternative, the code also builds six core-inflation measures from `InflSubyacente.xlsx` (the components `IEV`, `IMT`, `IRV`, `IRP`, `IEF`, and their average); the `IEF` core measure is used in the core-inflation reestimation (Appendix C). Each core series carries the same model code `infCR` and substitutes for headline inflation one at a time.

**Costa Rican output gap (`gapCR`).** Built from the BCCR's monthly real GDP series (`PIBreal.xlsx`, sheet *Mensuales*, chained-volume measure with 2022 reference year). The series is seasonally adjusted with X-13ARIMA-SEATS (Appendix E.5), and the gap is the percentage deviation of the log seasonally adjusted level from its Hodrick–Prescott trend, $100\,(\log x_t^{\mathrm{SA}} - \tau_t)$, with $\lambda = 15{,}917$. Projected months beyond the current month (`PIBreal.xlsx` extends to 2031) are dropped before filtering.

**Monetary-policy rate (`tpm`).** The BCCR monetary-policy rate (*tasa de política monetaria*, `TPM.xlsx`) is aggregated to monthly in levels, without further transformation.

## E.4 The Hodrick–Prescott trend

For the two output gaps the trend $\tau = (\tau_1, \ldots, \tau_n)'$ solves the standard penalized least-squares problem

$$\min_{\tau} \sum_{t=1}^{n} (x_t - \tau_t)^2 \;+\; \lambda \sum_{t=3}^{n} \left[(\tau_t - \tau_{t-1}) - (\tau_{t-1} - \tau_{t-2})\right]^2, \tag{8}$$

with closed-form solution $\tau = (I + \lambda D'D)^{-1}x$, where $D$ is the second-difference operator, $x$ is the log level, and the gap is $100(x - \tau)$. We use $\lambda = 1600$, the conventional Hodrick–Prescott (1997) constant, for the quarterly U.S. series, and $\lambda = 15{,}917$ for the monthly Costa Rican series—the Costa Rica-specific monthly smoothing parameter estimated by Gómez-Rodríguez (2023), who report $\lambda = 1{,}677$ for quarterly and $\lambda = 15{,}917$ for monthly Costa Rican real GDP.[7]

## E.5 Seasonal adjustment of the Costa Rican output gap

The monthly real GDP underlying `gapCR` is seasonally adjusted with X-13ARIMA-SEATS prior to detrending, so that the resulting output gap reflects the cyclical position of output rather than

[7] An earlier version of the pipeline applied the quarterly-calibrated value ($\lambda = 1{,}677$) directly to the monthly series; the current specification uses the monthly-calibrated value from the same source instead, at the correct frequency.

within-year calendar variation—the standard approach when an output gap is constructed from a monthly activity series.

The adjustment is applied to the real-GDP *level* using the U.S. Census Bureau X-13ARIMA-SEATS program with automatic ARIMA-model and outlier selection (the latter accommodating the 2020 pandemic disruption). In the pipeline it is run through the R `seasonal` package and the bundled `x13binary` executable: the routine `Data/sa_x13.R` returns the seasonally adjusted level, which `PrepareData.m` then logs and HP-filters as in Appendix E.4 ($\lambda = 15{,}917$). The adjusted series is recomputed from the current raw data and cached to `Data/PIBrealSA.csv`. The seasonally adjusted gap is the series shown for `gapCR` in Figure E.1.

## E.6 Frequency, aggregation, and sample

The model frequency is quarterly, the lowest among the ten series (imposed by the quarterly U.S. output gap). Higher-frequency series are aggregated to quarterly by the last-value-in-period convention in the baseline, and by a within-quarter mean in a robustness variant. After aggregation the ten series are synchronized on the intersection of their dates and rows with any missing value are removed, yielding a balanced panel over 2009Q1–2026Q2 ($T = 70$). Although the historical decomposition is read over the inflation-targeting period 2018–2026, the model is estimated over the full common sample to sharpen the estimation of the dynamics.

## E.7 Reproducibility

The raw inputs are the files listed in Table E.1 (`MatPrimInt.xlsx`, `GDPC1.csv`, `InflSC.xlsx`, `EFFR.csv`, `WuXiaShadowRate.xlsx`, `TCN.xlsx`, `EXPINFL60.xlsx`, `IPC_tasa_variacion.xlsx`, `PIBreal.xlsx`, `TPM.xlsx`, and—for the core-inflation robustness—`InflSubyacente.xlsx`). Running `PrepareData.m` regenerates the derived series and caches the seasonally adjusted GDP to `Data/PIBrealSA.csv`; the X-13 step requires R with the `seasonal` and `x13binary` packages, and the pipeline uses the cached seasonally adjusted series when R is unavailable. `CreateVAR.m` assembles the estimation matrix and `main.m` runs the full estimation and identification.