Evaluating Emerging Markets' Monetary Policy

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Abstract: Are emerging markets' central banks credibly committed to inflation targeting? This paper applies the "Optimal Policy Perturbation" (OPP) framework of Barnichon and Mesters (2023) to evaluate monetary policy credibility across emerging economies. Combining impulse responses from a Bayesian VAR with professional forecasts from the Economist Intelligence Unit, I exploit the dual interpretation of the OPP statistic. First, under the assumption that observed policy rates are locally optimal given policymakers' information sets, I adopt a revealed-preference approach and recover time-varying implicit policy weights by minimizing deviations of the OPP statistic from zero. Second, under fixed benchmark weights, I use the OPP statistic to assess whether policy rates could have been adjusted to further reduce the policymaker's loss, and to quantify the direction and magnitude of such adjustments. The evidence indicates that inflation-target regimes in emerging markets have become increasingly credible since the early 2000s, with stronger anchoring of inflation expectations and reduced inflation persistence. While central banks face sharper trade-offs during global crises, monetary policy behavior typically reverts toward inflation stabilization, highlighting the flexibility and resilience of modern inflation-target frameworks.

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1 Introduction

Are inflation-target regimes in emerging markets credible? Since the early 2000s, central banks around the world have increasingly adopted monetary frameworks centered on price stability, often with explicit numerical inflation targets. While advanced economies typically operate under clear legal mandates and strong institutional independence, emerging markets face structurally different constraints. They are more exposed to external shocks, rely more heavily on export-led growth, carry substantial foreign currency denominated debt, and often operate under political pressure. These features raise doubts about whether formal inflation targets meaningfully constrain policy in practice.

When difficult trade-offs arise, do central banks in emerging markets honor their stated commitment to price stability, or do they systematically deviate in favor of other objectives, such as supporting output or stabilizing the exchange rate? Such deviations matter because policy credibility shapes expectation formation, which in turn affects monetary transmission through both conventional tools (e.g., interest rates) and unconventional tools (e.g., forward guidance), especially near the zero lower bound.

This paper builds on the sufficient statistics framework of Barnichon and Mesters (2023) to evaluate the credibility of inflation-target regimes in emerging markets. They show that, given (i) empirical impulse responses of macroeconomic variables to a monetary policy shock and (ii) forecasts of future economic paths, one can construct a sufficient statistic—the "Optimal Policy Perturbation (OPP)"—that assesses whether the observed policy rate is locally optimal. Intuitively, if no small deviation in the policy rate can improve the central bank's loss function under expected future outcomes, the observed policy rate is internally consistent and therefore credible.

The logic of the OPP framework is closely related to first-order optimality conditions. In a single-variable setting, optimality requires that the derivative of the objective function with respect to the policy instrument equals zero. In a multivariate setting, local optimality

requires the gradient of the objective function to be zero. If a small perturbation to the policy rate could move the gradient closer to zero, then the observed policy rate is not locally optimal. The magnitude and sign of this perturbation summarize both the direction and strength of the policy adjustment that would further reduce the central bank's welfare loss.

A central contribution of this paper is to exploit the *dual interpretation* of the OPP statistic. Under the assumption that policymakers are cautious and generally avoid unnecessary policy changes, observed policy rates can be treated as approximately optimal. I therefore adopt a revealed-preference approach to recover the implied policy priorities: assuming observed policy rates are optimal, I solve for the weight vector on output, inflation, and depreciation that rationalizes the observed policy rate at each point in time by minimizing the OPP deviation from zero. If a central bank claims to prioritize inflation stabilization, yet the implied policy weights place most emphasis on exchange rate stability, this constitutes strong empirical evidence against credibility.

This approach is particularly well suited to emerging markets, where policy objectives are rarely explicit or stable. Unlike the Federal Reserve's dual mandate—often stylized as equal weights on inflation and employment—there is no clear benchmark loss function. Historical episodes such as the 1997 Asian Financial Crisis and the 2013 Taper Tantrum suggest that exchange-rate stabilization is often an implicit objective. I therefore define monetary policy as credible if observed policy rates can be rationalized by forecasted outcomes under a stable weighting of output, inflation, and depreciation over time.

Operationally, I develop an algorithm that recovers the implicit policy weights consistent with the observed policy rate in each period. While period-by-period estimates are naturally noisy, the implied weights exhibit systematic and economically meaningful patterns when examined across time and across regimes—for example, before and after inflation-target adoption or during financial crisis episodes.

The OPP framework also admits a complementary interpretation. Instead of recovering the implicit policy weights, one can impose some fixed weight vectors representing externally

imposed benchmarks, such as an inflation-target benchmark $\left(\frac{1}{2}, \frac{1}{2}, 0\right)$, an equal-weight benchmark $\left(\frac{1}{3}, \frac{1}{3}, \frac{1}{3}\right)$, or a global-optimal benchmark defined as the weight vector that minimizes the sum of squared OPP deviations from zero across all periods. Under each benchmark, the OPP statistic identifies the direction and magnitude of the policy rate adjustment that would improve central bank's welfare. When different benchmarks agree on the sign of the OPP, this provides robust evidence that observed policy was not locally optimal. When benchmarks disagree, this reveals the underlying trade-offs faced by the central bank. Reassuringly, the main credibility conclusions in this paper are robust across these alternative benchmarks.

The empirical implementation proceeds in two steps. First, I use a Bayesian autoregression (Bayesian VAR) to estimate impulse responses of output, inflation, and depreciation to a monetary policy shock for twelve inflation-target emerging economies. Unlike local projections, which estimate each horizon independently, the Bayesian VAR delivers joint posterior distributions of impulse response estimates across horizons, allowing coherent inference for OPP statistics over time. Moreover, since high-frequency monetary policy shocks are largely unavailable for emerging markets, I use a recursive (Cholesky) identification scheme that orders the policy rate last.

Second, I construct expected future paths using forecasts from the Economist Intelligence Unit (EIU). Unlike Barnichon and Mesters (2023), who rely on internal Federal Reserve forecasts, comparable official projections are unavailable for most emerging markets. The EIU forecasts offer three advantages: broad cross-country coverage since the mid-1990s, consistent methodology across countries, and institutional independence from domestic political pressures.

The results provide several new insights. I document strong evidence that many emerging markets have gradually placed increasing and more stable weight on inflation stabilization over time. This pattern is particularly pronounced in countries such as Brazil and Mexico, which experienced chronic high inflation in earlier decades. During crisis episodes, some central banks temporarily shift weight toward output stabilization, but many revert

quickly to inflation-focused behavior, suggesting flexibility rather than abandonment of the inflation-target framework during distressed times.

The framework also highlights underperformance. For example, for South Korea, all benchmarks indicate that policy rates should have been lowered more aggressively during the 2008 Global Financial Crisis. For Turkey, all benchmarks consistently imply that policy rates should have been tighter, especially since the early 2020s, coinciding with rising political interference. In small open economies such as Israel, I find evidence of a shift toward output stabilization following the Israel–Gaza conflict, illustrating how geopolitical risks shape monetary trade-offs.

The approach has limitations. First, the EIU forecasts are not equivalent to central banks' internal projections, though they provide consistent cross-country coverage and may be less politically distorted than official data in some settings. Second, policy instruments are also measured imperfectly across countries, as many emerging markets target collateralized or longer-maturity rates rather than overnight interbank rates, and operational frameworks have evolved over time. These issues introduce noise but do not undermine the central contribution: providing a transparent, comparable, and theory-consistent measure of monetary policy credibility where strong institutional benchmarks are absent.

1.1 Related Literature

This paper builds on the literature evaluating optimal monetary policy and credibility, building directly on the OPP framework of Barnichon and Mesters (2023). Its central contribution is extending this framework to emerging markets, where policy objectives are often opaque and institutional constraints are more severe.

A large literature emphasizes that emerging markets systematically deviate from textbook inflation-target behavior. Calvo and Reinhart (2002) document widespread "fear of floating": low exchange-rate volatility combined with high volatility in interest rates and reserves. Fraga, Goldfajn and Minella (2003) argue that emerging markets face greater

macroeconomic volatility, weaker credibility, and larger external exposure, necessitating more flexible inflation-target frameworks. Reviews by Svensson (2010) and Gill Hammond (2012) emphasize credibility, transparency, and flexibility as central pillars of successful inflation-target regimes.

On the theoretical side, Svensson (1997) shows that inflation-forecast targeting dominates both money growth and exchange rate targeting. Ghosh, Ostry and Chamon (2016) argue that sterilized foreign exchange intervention can be compatible with inflation-target and may even enhance credibility when capital mobility is imperfect.

The empirical evidence on inflation-target remains mixed. Mishkin and Schmidt-Hebbel (2007) find that inflation-target countries achieve lower long-run inflation and reduced sensitivity to external shocks. By contrast, Zhang and Wang (2022) and Bhalla, Bhasin and Loungani (2023) find limited short-run macroeconomic improvements following adoption and cannot reject mean reversion. Critics argue that inflation-target may come at the expense of output or financial stability, though Walsh (2009) finds no increase in output volatility and suggests that emerging markets may benefit more than advanced economies.

Rather than evaluating the average effectiveness of inflation-target, this paper focuses on the *credibility*. Credibility matters because expectations play a central role in inflation persistence and monetary transmission, especially as forward guidance becomes more important (Bems et al., 2021; Baxa, Horváth and Vašíček, 2014). The closest paper is Uribe et al. (2025), who show that post-adoption behavior is path-dependent: countries with histories of high inflation respond more aggressively to deviations even under formally credible regimes.

The remainder of the paper is organized as follows. Section 2 presents the methodology. Section 3 describes the empirical framework. Section 4 introduces the data. Section 5 reports the results. Section 6 concludes.

2 Methodology

This section presents the empirical framework used to construct optimal policy perturbation (OPP) statistics. The OPP statistic requires two sufficient statistics: (i) $\mathcal{R}^0$, the impulse responses of macroeconomic variables to a monetary policy shock under the baseline policy rule ϕ^0; and (ii) $\mathcal{Y}_t^0$, the forecast paths of these variables under the baseline rule ϕ^0 in the absence of a policy perturbation (i.e., $\delta_t = 0$).

Section 2.1 motivates the OPP statistic in a simple open-economy New Keynesian model. Section 2.3 explains how I use EIU forecasts to proxy forecast path $\mathcal{Y}_t^0$. Sections 2.4 describe the Bayesian VAR, the recursive (Cholesky) identification scheme, and the construction of the impulse responses $\mathcal{R}^0$. Section 2.5 combines these objects to compute the OPP time series and credible intervals.

2.1 Motivation: A simple four-equation New Keynesian model

To motivate the OPP statistic, consider a discretionary New Keynesian (NK) model in a small open economy setting (Galí, 2015; Barnichon and Mesters, 2023). The model consists of an investment-saving (IS) curve, a New Keynesian Phillips curve (NKPC), an uncovered interest parity (UIP) condition, and a baseline Taylor-style monetary policy (MP) rule.[1] The system is given as follows:

[1]The seminal paper by Gali and Monacelli (2005) shows that under certain conditions (e.g., log utility, unit elasticity of substitution between home and foreign good, and producer currency pricing), the optimal monetary policy of a small open economy is the domestic inflation targeting rule without an explicit exchange rate term. Moreover, Taylor (2001) argues that including the exchange rate directly in a Taylor rule need not improve macro stabilization because exchange rate movements already affect inflation dynamics (e.g., through the $\gamma\Delta\varepsilon_t$ term in the NKPC), and an explicit exchange rate term in the monetary policy rule may induce excessive interest rate volatility.

$$
\begin{aligned}
\text{(IS)} \qquad & x_t = \mathbb{E}_t\left[x_{t+1}\right] - \tfrac{1}{\sigma}\left(i_t - \mathbb{E}_t[\pi_{t+1}]\right) \\
\text{(NKPC)} \qquad & \pi_t = \mathbb{E}_t[\pi_{t+1}] + \kappa x_t + \gamma \Delta\varepsilon_t + \xi_t \\
\text{(UIP)} \qquad & \Delta\varepsilon_t = i_t + \eta_t \\
\text{(MP}^0\text{)} \qquad & i_t^0 = \phi^0 \pi_t + \epsilon_t^{\text{MP}} \\
\text{(MP-OPP)} \qquad & i_t = i_t^0 + \delta_t = \phi^0 \pi_t + \epsilon_t^{\text{MP}} + \delta_t
\end{aligned}
$$

where x_t is the output gap, π_t is inflation, $\Delta\varepsilon_t$ is the currency depreciation rate, and i_t is the monetary policy rate. The shocks $(\xi_t, \eta_t, \epsilon_t^{\text{MP}})$ are a cost-push shock, a UIP wedge shock, and a monetary policy shock respectively. The parameter ϕ^0 governs the baseline monetary policy rule. Relative to the textbook three-equation NK model, the key difference is the UIP wedge η_t and its transmission to inflation through the NKPC.[2]

The OPP statistic δ_t represents an infinitesimal deviation from the baseline policy rate. It is introduced to examine whether a marginal adjustment in the policy instrument would reduce the central bank's loss. At a local optimum, the gradient of the central bank's loss function with respect to the policy instrument—evaluated at the observed policy rate—should equal zero (a necessary but not sufficient condition for optimality). Equivalently, if a small disturbance δ_t can move this gradient closer to zero, then the observed policy rate is not locally optimal. In particular, the sign of δ_t indicates the direction of the welfare-improving policy adjustment, and its magnitude summarizes how strongly the data call for that adjustment.

Under discretionary monetary policy, $\mathbb{E}_t\left[x_{t+1}\right]$ and $\mathbb{E}_t\left[\pi_{t+1}\right]$ are taken as given. In this simple environment, the effect of δ_t on contemporaneous macro outcomes admits a closed-form solution—the endogenous variables $(x_t, \pi_t, \Delta\varepsilon_t, i_t)$ can be solved as linear functions of

[2] A standard UIP condition is $\mathbb{E}_t\left[\Delta\varepsilon_{t+1}\right] = i_t - i_t^* + \zeta_t$, where ζ_t is a wedge that reconciles the empirical deviations from the UIP condition. For a small open economy, I treat the foreign interest rate i_t^* and the UIP wedge ζ_t as exogenous and absorb $(-i_t^* + \zeta_t)$ into a single exogenous shock η_t.

the exogenous shocks $(\xi_t, \eta_t, \epsilon_t^{\text{MP}})$ and the policy perturbation δ_t:

$$\begin{aligned}
x_t &= -\frac{\phi^0}{\sigma\Lambda^0}\xi_t - \frac{\gamma\phi^0}{\sigma\Lambda^0}\eta_t - \frac{1}{\sigma\Lambda^0}\epsilon_t^{\text{MP}} - \frac{1}{\sigma\Lambda^0}\delta_t \\
\pi_t &= \frac{1}{\Lambda^0}\xi_t + \frac{\gamma}{\Lambda^0}\eta_t + \frac{\gamma - \kappa/\sigma}{\Lambda^0}\epsilon_t^{\text{MP}} + \frac{\gamma - \kappa/\sigma}{\Lambda^0}\delta_t \\
\Delta\varepsilon_t &= \frac{\phi^0}{\Lambda^0}\xi_t + \frac{1 + (\kappa/\sigma)\phi^0}{\Lambda^0}\eta_t + \frac{1}{\Lambda^0}\epsilon_t^{\text{MP}} + \frac{1}{\Lambda^0}\delta_t \\
i_t &= \frac{\phi^0}{\Lambda^0}\xi_t + \frac{\gamma\phi^0}{\Lambda^0}\eta_t + \frac{1}{\Lambda^0}\epsilon_t^{\text{MP}} + \frac{1}{\Lambda^0}\delta_t
\end{aligned}$$

where $\Lambda^0 \equiv 1 - (\gamma - \kappa/\sigma)\phi^0$ is a function that depends on the baseline rule ϕ^0 and other structural parameters.

Let $\mathbf{y}_t \equiv (x_t, \pi_t, \Delta\varepsilon_t)' \in \mathbb{R}^3$ collect the endogenous variables. Define the coefficient vectors $\Gamma^0 \equiv \frac{1}{\Lambda^0}\left(-\frac{\phi^0}{\sigma},\, 1,\, \phi^0\right)'$, $\Psi^0 \equiv \frac{1}{\Lambda^0}\left(-\frac{\gamma\phi^0}{\sigma},\, \gamma,\, 1 + \frac{\kappa\phi^0}{\sigma}\right)'$, and $\mathcal{R}^0 \equiv \frac{1}{\Lambda^0}\left(-\frac{1}{\sigma},\, \gamma - \frac{\kappa}{\sigma},\, 1\right)'$, where $\Gamma^0, \Psi^0, \mathcal{R}^0 \in \mathbb{R}^3$. Then the above equilibrium can be written compactly as

$$\mathbf{y}_t = \underbrace{\Gamma^0\xi_t + \Psi^0\eta_t + \mathcal{R}^0\epsilon_t^{\text{MP}}}_{\equiv\mathcal{Y}_t^0} + \mathcal{R}^0\delta_t \tag{1}$$

Equation (1) decomposes outcomes into two components: (i) $\mathcal{Y}_t^0$, the baseline forecast path of macroeconomic outcomes implied by the baseline rule ϕ^0 and the realized shocks $\left(\xi_t, \eta_t, \epsilon_t^{\text{MP}}\right)$; and (ii) $\mathcal{R}^0\delta_t$, the deviation from that baseline forecast path induced by an arbitrary policy perturbation δ_t added to the baseline monetary rule.

Intuitively, in the absence of cost-push and exchange-rate shocks (i.e., $\xi_t = 0$ and $\eta_t = 0$), the term $\mathcal{R}^0\epsilon_t^{\text{MP}}$ in $\mathcal{Y}_t^0$ represents the contemporaneous impulse responses of macroeconomic outcomes $\mathbf{y}_t$ to a one-unit monetary policy shock ϵ_t^{MP} under the baseline rule ϕ^0. By contrast, $\mathcal{R}^0\delta_t$ captures the marginal effect of an infinitesimal policy perturbation δ_t on the macroeconomic outcomes.

Most importantly, both the monetary policy shock ϵ_t^{MP} and the policy perturbation δ_t affect macroeconomic outcomes $\mathbf{y}_t$ through the same coefficient vector $\mathcal{R}^0$. This equivalence underpins the sufficient statistics approach: empirical impulse responses to a monetary policy

shock can be used to characterize how a marginal policy perturbation shifts macroeconomic outcomes, and therefore how it alters the central bank's loss function.

2.2 Central bank loss function and optimal policy perturbation

This subsection shows how the policy perturbation δ_t can be used to assess whether observed policy is locally optimal, or equivalently, whether there exists scope for improving policy implementation. I assume the central bank operates under a flexible inflation-target regime and evaluates outcomes using a standard quadratic loss function over the output gap, inflation, and exchange rate depreciation (Svensson, 2010):

$$\mathcal{L}_t \equiv \tfrac{1}{2}\mathbf{y}_t'\mathbf{W}\mathbf{y}_t = \tfrac{1}{2}\left(\omega^x x_t^2 + \omega^\pi \pi_t^2 + \omega^\varepsilon \Delta\varepsilon_t^2\right),$$

where $\mathbf{W} \equiv \text{diag}(\omega^x, \omega^\pi, \omega^\varepsilon) \in \mathbb{R}^{3\times 3}$, $\omega^x + \omega^\pi + \omega^\varepsilon = 1$, and $\omega^x, \omega^\pi, \omega^\varepsilon \geq 0$.

Following the delegation logic of Rogoff (1985), I introduce a social planner who evaluates whether the observed policy rate is internally consistent with the central bank's stated objectives. The social planner asks whether a small perturbation δ_t to the policy rule could further reduce the central bank's loss. Using $\mathbf{y}_t = \mathcal{Y}_t^0 + \mathcal{R}^0\delta_t$ from Equation 1, the social planner's problem is

$$\min_{\delta_t \in \mathbb{R}} \ \mathcal{L}_t = \tfrac{1}{2}\mathbf{y}_t'\mathbf{W}\mathbf{y}_t \qquad \text{s.t.} \quad \mathbf{y}_t = \mathcal{Y}_t^0 + \mathcal{R}^0\delta_t.$$

The first-order condition yields the (scalar) optimal policy perturbation

$$\delta_t^* = -\left(\mathcal{R}^{0\prime}\mathbf{W}\mathcal{R}^0\right)^{-1}\left(\mathcal{R}^{0\prime}\mathbf{W}\mathcal{Y}_t^0\right), \qquad \delta_t^* \in \mathbb{R}. \tag{2}$$

Consistent with the discussion in Section 2.1, Equation (2) shows that computing the OPP statistic requires two inputs: (i) the baseline forecast path $\mathcal{Y}_t^0$ implied by the baseline policy rule under full information about all realized shocks; and (ii) the impulse response

$\mathcal{R}^0$, which maps both a monetary policy shock and a marginal policy perturbation into macroeconomic outcomes.

The derivation above focuses on the contemporaneous horizon ($h = 0$). In practice, however, monetary policy affects macroeconomic outcomes over multiple future horizons, and central banks care about the entire forecast path rather than only contemporaneous outcomes.

Accordingly, I generalize (2) to a multi-horizon setting by stacking forecast paths and impulse responses of macroeconomic variables $n = 1, 2, \ldots, N$ over horizons $h = 0, 1, \ldots, H$, so that $\mathcal{Y}_t^0 \in \mathbb{R}^{N(H+1)}$ and $\mathcal{R}^0 \in \mathbb{R}^{N(H+1)}$. The simple New Keynesian example above corresponds to the special case $N = 3$ and $H = 0$, while the empirical implementation in Sections 2.3 and 2.4 allows both dimensions to be unrestricted.

2.3 EIU forecasts data as proxies for the counterfactual path $\mathcal{Y}_t^0$

Sections 2.1 and 2.2 both interpret the variable $\mathcal{Y}_t^0$ as the expected evolution of macroeconomic outcomes under the baseline policy rule ϕ^0, given full information about all realized shocks $\left(\xi_t, \eta_t, \epsilon_t^{\text{MP}}\right)$ and in the absence of any policy perturbation (i.e., $\delta_t = 0$).[3] Under this interpretation, $\mathcal{Y}_t^0$ represents the counterfactual path that would prevail if the central bank implemented its announced policy rule and private agents formed expectations using all available information about relevant exogenous shocks.

I proxy this object $\mathcal{Y}_t^0$ using professional forecasts, interpreted as expectations formed using comprehensive contemporaneous information about macroeconomic conditions, external shocks, and the prevailing baseline policy rule (e.g., inflation-target). Under this interpretation, the reported EIU forecast paths summarize the expected trajectory of the economy under the baseline policy rule, in the absence of policy perturbations.[4]

EIU reports provide annual (calendar-year; end-of-year) forecasts for output, inflation,

[3] Importantly, the baseline rule need not be optimal.

[4] Barnichon and Mesters (2023) use the Federal Reserve's internal Greenbook forecasts, which they interpret as reflecting policymakers' information set under the baseline rule. Comparable internal forecasts are not publicly available for central banks in emerging markets.

depreciation, and other macroeconomic variables up to five years ahead. These forecasts are observed at discrete horizons $h \in \{0, 4, 8, 12, 16, 20\}$ quarters. I therefore set the maximum horizon to $H = 20$ in both the Bayesian VAR and the forecast data and linearly interpolate to obtain quarterly forecasts at all horizons $h = 0, 1, \ldots, 20$.

To be specific, let $y_{t,h}^{0,n,\text{int}}$ denote the interpolated scalar forecast for variable n at horizon h, made at year-quarter t.[5] I construct deviations from the long-run forecast $y_{t,H+1}^{0,n,\text{int}}$ and define $\tilde{y}_{t,h}^{0,n} \equiv y_{t,h}^{0,n,\text{int}} - y_{t,H+1}^{0,n}$. Stacking these deviations across all N variables and all $H+1$ horizons yields the vector $\widetilde{\mathcal{Y}}_t^0 \in \mathbb{R}^{N(H+1)}$ at year-quarter t:

$$\widetilde{\mathcal{Y}}_t^0 \equiv \begin{pmatrix} \tilde{\mathbf{y}}_{t,0}^0 \\ \tilde{\mathbf{y}}_{t,1}^0 \\ \vdots \\ \tilde{\mathbf{y}}_{t,H}^0 \end{pmatrix} \in \mathbb{R}^{N(H+1)}, \qquad \tilde{\mathbf{y}}_{t,h}^0 \equiv \begin{pmatrix} y_{t,h}^{0,1,\text{int}} - y_{t,H+1}^{0,1} \\ y_{t,h}^{0,2,\text{int}} - y_{t,H+1}^{0,2} \\ \vdots \\ y_{t,h}^{0,N,\text{int}} - y_{t,H+1}^{0,N} \end{pmatrix} \in \mathbb{R}^N.$$

To incorporate forecast uncertainty, I follow Barnichon and Mesters (2023) and model the baseline forecast path as a random vector centered on the observed forecast path. To be specific, I assume

$$\mathcal{Y}_t^{0,(m)} \sim \mathcal{N}\left(\widetilde{\mathcal{Y}}_t^0,\ \Omega \otimes I_N\right), \qquad m = 1, \ldots, M,$$

where $\mathcal{Y}_t^{0,(m)}$ represents the empirical counterpart to the theoretical object $\mathcal{Y}_t^0$ in each draw. The matrix $\Omega \in \mathbb{R}^{(H+1)\times(H+1)}$ captures correlation across horizons and is specified as

$$\Omega = \left[\rho^{|k-j|}\right]_{k,j=0}^{H}, \qquad \rho = 0.9.$$

This AR(1)-type structure captures the idea that forecast errors at nearby horizons are more highly correlated than those at distant horizons. The simulated draws $\{\mathcal{Y}_t^{0,(m)}\}_{m=1}^M$ are used to propagate forecast uncertainty into the distribution of the OPP statistic.

[5] In particular, $y_{t,4}^{0,n,\text{int}}$, $y_{t,8}^{0,n,\text{int}}$, $y_{t,12}^{0,n,\text{int}}$, $y_{t,16}^{0,n,\text{int}}$, and $y_{t,20}^{0,n,\text{int}}$ correspond to the published EIU forecasts at horizons $h = 4, 8, 12, 16, 20$.

2.4 Using Bayesian VAR to estimate impulse responses $\mathcal{R}^0$

This subsection describes the Bayesian VAR (BVAR) framework used to estimate the impulse responses $\mathcal{R}^0$ of macroeconomic variables to a one-unit monetary policy shock under the baseline policy rule ϕ^0. The formulation closely follows Koop (2010) and Geweke (2005). Section 2.4.1 defines the reduced-form VAR and its stacked regression representation. Section 2.4.2 introduces the Normal-Inverse-Wishart prior and posterior sampling. Section 2.4.3 details the recursive identification scheme. Section 2.4.4 constructs impulse responses using the companion-form representation.

Macroeconomic variables often interact both contemporaneously and with lags. A VAR therefore provides a flexible reduced-form representation of these joint dynamics without requiring a fully specified structural model (e.g., explicit assumptions about expectation formation or deep parameters). Under standard regularity conditions, the reduced-form lag coefficients can be consistently estimated. To map reduced-form innovations into economically meaningful monetary policy shocks, I impose a Recursive (Cholesky) identification that orders the policy rate last, corresponding to the assumption that the policy rate affects other macroeconomic variables only with a lag within the period.

I estimate the VAR in a Bayesian framework to obtain a joint posterior distribution over impulse responses across horizons. This joint posterior preserves the variance-covariance structure of impulse response estimates across horizons, which is important for coherently propagating uncertainty into the OPP statistic.[6]

2.4.1 Notations and timing conventions

A structural interpretation of the VAR is that the variables of interest are jointly determined by both contemporaneous and lagged values of all variables in the system, including them-

[6] I adopt a Bayesian VAR rather than local projections because local projections estimate each horizon separately and therefore do not preserve the cross-horizon variance-covariance structure by construction. Moreover, the Bayesian VAR posterior provides a natural way to propagate uncertainty into the OPP statistic via posterior simulation.

selves. Consider an L-lag structural VAR. For variable n in period t, its value y_t^n can be written as

$$y_t^n = \sum_{i=1}^{N} \alpha^{ni} y_t^i + \sum_{\ell=1}^{L} \left(\sum_{i=1}^{N} \phi_\ell^{ni} y_{t-\ell}^i \right) + \epsilon_t^n,$$

where ϵ_t^n denotes the structural shock to variable n at time t.

Rewriting the system in matrix form, define $\mathbf{y}_t \equiv (y_t^1, y_t^2, \cdots, y_t^N)' \in \mathbb{R}^N$ and $\boldsymbol{\epsilon}_t \equiv (\epsilon_t^1, \cdots, \epsilon_t^N)' \in \mathbb{R}^N$, and let $\mathbf{A} = (\alpha^{ni}) \in \mathbb{R}^{N \times N}$ and $\Phi_\ell = (\phi_\ell^{ni}) \in \mathbb{R}^{N \times N}$. The structural VAR can then be written compactly as

$$\mathbf{A}\mathbf{y}_t = \sum_{\ell=1}^{L} \Phi_\ell \mathbf{y}_{t-\ell} + \boldsymbol{\epsilon}_t.$$

Assuming that $\mathbf{A}$ is invertible, the system admits the reduced-form representation

$$\mathbf{y}_t = \sum_{\ell=1}^{L} \mathbf{B}_\ell \mathbf{y}_{t-\ell} + \mathbf{e}_t, \qquad \mathbf{B}_\ell \equiv \mathbf{A}^{-1}\Phi_\ell, \qquad \mathbf{e}_t \equiv \mathbf{A}^{-1}\boldsymbol{\epsilon}_t,$$

where $\mathbf{e}_t \in \mathbb{R}^N$ and $\mathbf{B}_\ell \in \mathbb{R}^{N \times N}$. I assume $\mathbb{E}[\mathbf{e}_t] = 0$ and $\mathbb{E}[\mathbf{e}_t \mathbf{e}_t'] \equiv \boldsymbol{\Sigma} \in \mathbb{R}^{N \times N}$.

Under standard regularity conditions, the reduced-form coefficients $\{\mathbf{B}_\ell\}_{\ell=1}^L$ can be consistently estimated. However, identification of the contemporaneous impact matrix $\mathbf{A}^{-1}$ requires additional assumptions, which I impose below using a recursive (Cholesky) identification in Section 2.4.3.

Stacking the system over time yields the regression form

$$\mathbf{Y} = \mathbf{X}\mathbf{B} + \mathbf{e},$$

where the matrix $\mathbf{Y} \in \mathbb{R}^{(T-L) \times N}$ stacks macroeconomic outcomes; the regressor matrix $\mathbf{X} \equiv (\mathbf{1} \mid \mathbf{Y}_1 \mid \cdots \mid \mathbf{Y}_L) \in \mathbb{R}^{(T-L) \times (1+NL)}$ stacks a row of ones $\mathbf{1}' \in \mathbb{R}^{1 \times N}$ and L lags of $\mathbf{Y}_\ell$; the coefficient matrix $\mathbf{B} \in \mathbb{R}^{(1+NL) \times N}$ stacks the intercept and lag matrices $\mathbf{B}_\ell \in \mathbb{R}^{N \times N}$; and the matrix $\mathbf{e} \in \mathbb{R}^{(T-L) \times N}$ stacks the reduced-form innovations. To be specific, their matrix

forms are given by:

$$\mathbf{Y} \equiv \mathbf{Y}_{L+1}, \qquad \mathbf{Y}_\ell \equiv \begin{pmatrix} \mathbf{y}_\ell' \\ \mathbf{y}_{\ell+1}' \\ \vdots \\ \mathbf{y}_{\ell+(T-L-1)}' \end{pmatrix}, \qquad \mathbf{B} = \begin{pmatrix} \mathbf{C}_0 \\ \mathbf{B}_1 \\ \vdots \\ \mathbf{B}_L \end{pmatrix}, \qquad \mathbf{e} \equiv \begin{pmatrix} \mathbf{e}_{L+1}' \\ \mathbf{e}_{L+2}' \\ \vdots \\ \mathbf{e}_T' \end{pmatrix}$$

where $\mathbf{y}_t' = \left(y_t^1, y_t^2, \cdots, y_t^N\right) \in \mathbb{R}^{1\times N}$, $\mathbf{e}_t' \equiv \left(e_t^1, e_t^2, \cdots, e_t^N\right) \in \mathbb{R}^{1\times N}$, and $\mathbf{X}$ is given by:

$$\mathbf{X} \equiv \begin{pmatrix} 1 & y_1^1 & \cdots & y_1^N & \cdots & y_L^1 & \cdots & y_L^N \\ \vdots & \vdots & \ddots & \vdots & & \vdots & \ddots & \vdots \\ 1 & y_{T-L}^1 & \cdots & y_{T-L}^N & \cdots & y_{T-1}^1 & \cdots & y_{T-1}^N \end{pmatrix} \in \mathbb{R}^{(T-L)\times(1+NL)}$$

At this stage, I only impose that the reduced-form innovations satisfy $\mathbb{E}[\mathbf{e}_t] = 0$ and $\mathbb{E}\left[\mathbf{e}_t\mathbf{e}_t'\right] = \mathbf{\Sigma}$, where $\mathbf{\Sigma} \in \mathbb{R}^{N\times N}$ is the symmetric positive-definite variance–covariance matrix

$$\mathbf{\Sigma} \equiv \begin{pmatrix} \mathbb{E}\left[\left(e_t^1\right)^2\right] & \cdots & \mathbb{E}\left[e_t^1 e_t^N\right] \\ \vdots & \ddots & \vdots \\ \mathbb{E}\left[e_t^N e_t^1\right] & \cdots & \mathbb{E}\left[\left(e_t^N\right)^2\right] \end{pmatrix} \in \mathbb{R}^{N\times N}$$

Note that $\mathbf{\Sigma}$ is related to the structural system via

$$\mathbf{\Sigma} = \mathbf{A}^{-1}\left(\mathbf{A}^{-1}\right)'.$$

The key implication is that estimation of the reduced-form VAR delivers $\mathbf{B}$ and $\mathbf{\Sigma}$, but does not identify the contemporaneous impact matrix $\mathbf{A}^{-1}$. Recovering $\mathbf{A}^{-1}$ therefore requires additional identifying assumptions, which I impose using the recursive (Cholesky) identification described in Section 2.4.3.

2.4.2 Bayesian VAR

Assume the reduced-form innovations $\{\mathbf{e}_t\}_{t=L+1}^{T}$ are independently and identically drawn from a normal distribution of mean $\mathbf{0} \in \mathbb{R}^N$ and variance-covariance matrix $\mathbf{\Sigma} \in \mathbb{R}^{N \times N}$ across time $t = L+1, \cdots, T$, that is,

$$\mathbf{e}_t \overset{\text{i.i.d.}}{\sim} \mathcal{N}(\mathbf{0}, \mathbf{\Sigma}) \qquad t = L+1, \ldots, T$$

Stacking over time yields the matrix-normal representation

$$\mathbf{e} \sim \mathcal{MN}(\mathbf{0}, I_{T-L}, \mathbf{\Sigma})$$

where the identity matrix I_{T-L} reflects the assumption that reduced-form innovations $(\mathbf{e}_t)_{t=L+1}^{T}$ are independent and identically distributed over time.

I adopt a conjugate Normal-Inverse-Wishart (NIW) prior. To be specific, the innovation variance-covariance matrix $\mathbf{\Sigma} \equiv \mathbb{E}[\mathbf{e}_t \mathbf{e}_t']$ follows

$$\mathbf{\Sigma} \sim \mathcal{IW}(\underline{\mathbf{S}}, \underline{\alpha})$$

where $\mathcal{IW}$ denotes the inverse-Wishart distribution, $\underline{\mathbf{S}} \in \mathbb{R}^{N \times N}$ is a symmetric positive definite scale matrix, and $\underline{\alpha}$ is the degrees of freedom parameter.

Conditional on $\mathbf{\Sigma}$, the coefficient matrix $\mathbf{B}$ follows a matrix-normal prior,

$$\mathbf{B} \mid \mathbf{\Sigma} \sim \mathcal{MN}(\underline{\mathbf{B}}, \underline{\mathbf{V}}, \mathbf{\Sigma}),$$

where $\underline{\mathbf{B}} \in \mathbb{R}^{(1+NL) \times N}$ is the prior mean matrix and $\underline{\mathbf{V}} \in \mathbb{R}^{(1+NL) \times (1+NL)}$ is a symmetric positive definite prior variance-covariance matrix. This Normal-Inverse-Wishart structure is conjugate and therefore delivers closed-form posterior updating.

Following an empirical Bayes approach, the hyperparameters governing the NIW prior—

most importantly the overall tightness parameter $\lambda(h)$—are selected by maximizing the marginal likelihood of the VAR, as in Giannone, Lenza and Primiceri (2015); Ferreira, Miranda-Agrippino and Ricco (2025); Miranda-Agrippino and Ricco (2021). The posterior remains NIW with closed-form updates. In particular, given prior parameters $(\underline{\mathbf{B}}, \underline{\mathbf{V}}, \underline{\mathbf{S}}, \underline{\alpha})$ and the observed data $(\mathbf{Y}, \mathbf{X})$, the joint posterior distribution of $\left(\boldsymbol{\Sigma}^{(d)}, \mathbf{B}^{(d)} \mid \boldsymbol{\Sigma}^{(d)}\right)$ remains Normal-Inverse-Wishart. In particular, it can be shown that

$$\boldsymbol{\Sigma}^{(d)} \mid \mathbf{Y}, \mathbf{X} \sim \mathcal{IW}(\overline{\mathbf{S}}, \overline{\alpha})$$

and, conditional on $\boldsymbol{\Sigma}^{(d)} \in \mathbb{R}^{N \times N}$,

$$\mathbf{B}^{(d)} \mid \boldsymbol{\Sigma}^{(d)}, \mathbf{Y}, \mathbf{X} \sim \mathcal{MN}(\overline{\mathbf{B}}, \overline{\mathbf{V}}, \boldsymbol{\Sigma}^{(d)}).$$

where the posterior parameters are given by

$$\begin{aligned}
\overline{\mathbf{V}} &= (\mathbf{X}'\mathbf{X} + \underline{\mathbf{V}}^{-1})^{-1} \\
\overline{\mathbf{B}} &= \overline{\mathbf{V}}(\mathbf{X}'\mathbf{Y} + \underline{\mathbf{V}}^{-1}\underline{\mathbf{B}}) \\
\overline{\mathbf{S}} &= \underline{\mathbf{S}} + \tfrac{1}{2}(\mathbf{Y}'\mathbf{Y} + \underline{\mathbf{B}}'\underline{\mathbf{V}}^{-1}\underline{\mathbf{B}} - \overline{\mathbf{B}}'\overline{\mathbf{V}}^{-1}\overline{\mathbf{B}}) \\
\overline{\alpha} &= \underline{\alpha} + (T - L).
\end{aligned}$$

Posterior inference is conducted by drawing

$$\left\{\left(\boldsymbol{\Sigma}^{(d)}, \mathbf{B}^{(d)} \mid \boldsymbol{\Sigma}^{(d)}\right)\right\}_{d=1}^{D}$$

from the posterior distribution.

2.4.3 Identification: Cholesky decomposition

This subsection describes how I use a recursive (Cholesky) identification scheme to map reduced-form posterior draws $\{(\boldsymbol{\Sigma}^{(d)}, \mathbf{B}^{(d)} \mid \boldsymbol{\Sigma}^{(d)})\}_{d=1}^{D}$ into structural impulse response func-

tions $\{\mathcal{R}^{(d)}\}_{d=1}^{D}$, where $\mathcal{R}^{(d)} \equiv \left(\mathcal{R}_0^{(d)}, \cdots, \mathcal{R}_H^{(d)}\right)' \in \mathbb{R}^{N(H+1)}$ with $\mathcal{R}_h^{(d)} \in \mathbb{R}^N$ for all impulse response draws $d = 1, \cdots, D$ and horizons $h = 0, 1, \cdots, H$.

Fix an arbitrary posterior draw $d \in \{1, \ldots, D\}$. This draw provides a reduced-form variance-covariance matrix of innovations $\mathbf{\Sigma}^{(d)} \in \mathbb{R}^{N \times N}$ with $\mathbb{E}[\mathbf{e}_t \mathbf{e}_t'] = \mathbf{\Sigma}^{(d)}$, as well as a corresponding lag coefficient matrix $\mathbf{B}^{(d)} \mid \mathbf{\Sigma}^{(d)} \in \mathbb{R}^{(1+NL) \times N}$.

Let $\boldsymbol{\epsilon}_t \in \mathbb{R}^N$ denote the vector of structural shocks, normalized such that $\mathbb{E}[\boldsymbol{\epsilon}_t] = \mathbf{0}$ and $\mathbb{E}[\boldsymbol{\epsilon}_t \boldsymbol{\epsilon}_t' \mid \mathcal{F}_{t-1}] = I_N$. Assume that reduced-form innovations $\mathbf{e}_t$ are linear combinations of structural shocks $\boldsymbol{\epsilon}_t$ through the contemporaneous impact matrix $\mathbf{A}^{-1}$:

$$\mathbf{e}_t = \mathbf{A}^{-1} \boldsymbol{\epsilon}_t.$$

Then the reduced-form variance-covariance matrix satisfies

$$\mathbf{\Sigma}^{(d)} = \mathbb{E}[\mathbf{e}_t \mathbf{e}_t'] = \mathbf{A}^{-1} \mathbb{E}[\boldsymbol{\epsilon}_t \boldsymbol{\epsilon}_t' \mid \mathcal{F}_{t-1}] (\mathbf{A}^{-1})' = \mathbf{A}^{-1} (\mathbf{A}^{-1})'.$$

For each posterior draw d, I therefore recover the corresponding contemporaneous impact matrix $\mathbf{A}^{-1,(d)}$ by applying the Cholesky decomposition to $\mathbf{\Sigma}^{(d)}$. To be specific, let $\mathbf{P}^{(d)}$ denote the lower-triangular Cholesky factor such that

$$\mathbf{\Sigma}^{(d)} = \mathbf{P}^{(d)} \mathbf{P}^{(d)\prime}.$$

I set $\mathbf{A}^{-1,(d)} \equiv \mathbf{P}^{(d)}$. This corresponds to a recursive identification scheme. The ordering of variables in $\mathbf{y}_t$ is chosen such that the policy rate appears last, implying that monetary policy can respond contemporaneously to all other variables in the system, while its effects on other variables occur with a lag within the period.

2.4.4 Constructing IRFs from the Bayesian VAR

To construct impulse responses for each posterior draw $d \in \{1, 2, \cdots, D\}$, I begin with the posterior draw of the reduced-form lag coefficient matrix $\mathbf{B}^{(d)} \mid \mathbf{\Sigma}^{(d)}$, which stacks both the intercept and lag coefficients:

$$\mathbf{B}^{(d)} \mid \mathbf{\Sigma}^{(d)} = \begin{pmatrix} \mathbf{C}_0^{(d)} \\ \mathbf{B}_1^{(d)} \\ \vdots \\ \mathbf{B}_L^{(d)} \end{pmatrix} \in \mathbb{R}^{(1+NL)\times N}$$

where $\mathbf{C}_0^{(d)} \in \mathbb{R}^{1\times N}$ is the intercept and each $\mathbf{B}_\ell^{(d)} \in \mathbb{R}^{N\times N}$ for $\ell = 1, \ldots, L$ is the individual lag coefficient matrix. Since the intercept captures only deterministic time-trend components, I drop the intercept matrix $\mathbf{C}_0^{(d)}$ and work exclusively with the lag matrices $\left(\mathbf{B}_\ell^{(d)}\right)_{\ell=1}^{L}$ when constructing impulse responses.

To represent the dynamics in a state-space (companion) form, first define the stacked state vector of impulse responses for posterior draw d at horizon h as

$$\mathbf{R}_h^{(d)} \equiv \begin{pmatrix} \mathbf{y}_h^{\text{IRF},(d)} \\ \mathbf{y}_{h-1}^{\text{IRF},(d)} \\ \vdots \\ \mathbf{y}_{h-L+1}^{\text{IRF},(d)} \end{pmatrix} \in \mathbb{R}^{NL}, \qquad \mathbf{y}_h^{\text{IRF},(d)} = \begin{pmatrix} y_h^{\text{IRF},1,(d)} \\ y_h^{\text{IRF},2,(d)} \\ \vdots \\ y_h^{\text{IRF},N,(d)} \end{pmatrix} \in \mathbb{R}^N.$$

where $y_h^{\text{IRF},n,(d)}$ denotes the impulse response of variable n at horizon h for posterior draw d, and $\mathbf{y}_h^{\text{IRF},(d)}$ stacks the impulse responses of all N variables at that horizon h for the posterior draw d.

Given the lag matrices $\left(\mathbf{B}_\ell^{(d)}\right)_{\ell=1}^{L}$, define the companion matrix for draw d as $\mathbf{F}^{(d)}$:

$$\mathbf{F}^{(d)} \equiv \begin{pmatrix} \mathbf{B}_1^{(d)} & \mathbf{B}_2^{(d)} & \cdots & \mathbf{B}_{L-1}^{(d)} & \mathbf{B}_L^{(d)} \\ I_N & \mathbf{0} & \cdots & \mathbf{0} & \mathbf{0} \\ \mathbf{0} & I_N & \cdots & \mathbf{0} & \mathbf{0} \\ \vdots & \vdots & \ddots & \vdots & \vdots \\ \mathbf{0} & \mathbf{0} & \cdots & I_N & \mathbf{0} \end{pmatrix} \in \mathbb{R}^{NL \times NL}$$

Let $\boldsymbol{\epsilon}_0^{MP} \in \mathbb{R}^N$ denote a unit monetary policy shock, defined as a vector with a one in the position corresponding to the policy rate (ordered last) and zeros elsewhere. The initial impact of a structural shock enters through the contemporaneous impact matrix $\mathbf{A}^{-1,(d)}$, so the state vector at impact is initialized as

$$\mathbf{R}_0^{(d)} \equiv \begin{pmatrix} \mathbf{A}^{-1,(d)} \boldsymbol{\epsilon}_0^{MP} \\ \mathbf{0} \\ \vdots \\ \mathbf{0} \end{pmatrix} \in \mathbb{R}^{NL}.$$

The impulse response dynamics then follow by iterating forward on the companion form:

$$\mathbf{R}_h^{(d)} = \mathbf{F}^{(d)} \mathbf{R}_{h-1}^{(d)}, \qquad h \geq 1.$$

For each posterior draw d, I collect the impulse responses across horizons $h = 0, 1, \ldots, H$ into the stacked vector

$$\mathcal{R}^{(d)} \equiv \begin{pmatrix} \mathcal{R}_0^{(d)} \\ \mathcal{R}_1^{(d)} \\ \vdots \\ \mathcal{R}_H^{(d)} \end{pmatrix} \in \mathbb{R}^{N(H+1)}, \qquad \mathcal{R}_h^{(d)} \in \mathbb{R}^N,$$

where each $\mathcal{R}_h^{(d)}$ corresponds to the first N elements of the state vector $\mathbf{R}_h^{(d)}$ and therefore represents the impulse responses of all N variables at horizon h. Notice that the impulse response object $\mathcal{R}^{(d)}$ is time-invariant: it does not vary across year-quarter t, in contrast to the forecast-path object $\mathcal{Y}_t^{0,(m)}$, which varies over year-quarter t.

Throughout the analysis, I estimate the Bayesian VAR for each country using only observations from the post-inflation-target period. Accordingly, the resulting impulse response draws $\{\mathcal{R}^{0,(d)}\}_{d=1}^{D}$ correspond to the baseline inflation-target policy regime, where the superscript 0 denotes the inflation-target baseline rule.

2.5 Implementation

This subsection translates the theoretical framework into an empirical procedure. The key implication of Sections 2.3 and 2.4 is that, empirically, the OPP statistic δ_t depends on two sufficient statistics:

1. $\{\mathcal{R}^{0,(d)}\}_{d=1}^{D}$, where each $\mathcal{R}^{0,(d)} \in \mathbb{R}^{N(H+1)}$ is a posterior draw of impulse response coefficients to a one-unit monetary policy shock under the baseline policy rule ϕ^0;

2. $\{\mathcal{Y}_t^{0,(m)}\}_{m=1}^{M}$, where each $\mathcal{Y}_t^{0,(m)} \in \mathbb{R}^{N(H+1)}$ is a draw of the forecast path under the same baseline rule ϕ^0

Given the collections of draws $\{\mathcal{R}^{0,(d)}\}_{d=1}^{D}$ and $\{\mathcal{Y}_t^{0,(m)}\}_{m=1}^{M}$, I compute the (scalar) OPP statistic for each pair (m, d) as

$$\delta_t^{*,(m,d)} \equiv -\left(\mathcal{R}^{0,(d)\prime}\mathbf{W}\mathcal{R}^{0,(d)}\right)^{-1}\left(\mathcal{R}^{0,(d)\prime}\mathbf{W}\mathcal{Y}_t^{0,(m)}\right) \in \mathbb{R}^1 \tag{3}$$

Uncertainty is summarized using posterior quantiles of the distribution of $\{\delta_t^{*,(m,d)}\}$ across all (m, d) at each year-quarter t. To be specific, I report the 68th, 90th, and 95th credible intervals (equal-tailed).

3 Empirical Strategy

This section explains how I use the dual interpretation of the OPP statistic to evaluate inflation-target monetary policy in emerging markets. The analysis proceeds in two steps.

First, Section 3.1 adopts a revealed-preference approach. I assume that, in each period, the observed policy rate is optimal given the central bank's contemporaneous policy priorities and information set. Under this assumption, I recover the period-specific policy weight vector that minimizes deviations of the OPP statistic from zero. The resulting time series of weights summarizes the evolution of implicit trade-offs across output, inflation, and exchange rate stabilization. This framework allows me to study how policy priorities evolve around the adoption of inflation targeting and during crisis episodes. I also test whether the inferred inflation weight is statistically consistent with the benchmark value of 0.5 implied by a standard dual-mandate framework.

Second, Section 3.2 imposes time-invariant policy priorities and asks a different question: under fixed weights, is there systematic evidence of policy misalignment? I consider three benchmark weight schemes: an inflation-target benchmark $\left(\frac{1}{2}, \frac{1}{2}, 0\right)$, an equal-emphasis benchmark $\left(\frac{1}{3}, \frac{1}{3}, \frac{1}{3}\right)$, and a globally optimal benchmark that minimizes the sum of squared deviations of the OPP statistic from zero across periods.

3.1 Revealed preference: period-specific optimal weights

In many emerging markets, formal policy mandates are incomplete or opaque, making it difficult to assess credibility by directly comparing observed actions to an explicit loss function. Instead, I infer the implicit policy priorities from observed policy rates and forecast data.

As an illustrative example, under a credible inflation-target framework, the recovered policy weights should resemble $\left(\frac{1}{2}, \frac{1}{2}, 0\right)$. If instead the estimated weight vector that rationalizes the observed policy rate is much closer to $(1, 0, 0)$, this would indicate that the central bank primarily prioritizes output stabilization, contradicting its stated inflation-target

commitment.

Formally, I recover the period-specific implicit trade-offs summarized by the weight vector

$$\boldsymbol{\omega}_t \equiv (\omega_t^x, \omega_t^\pi, \omega_t^\varepsilon), \qquad \omega_t^x + \omega_t^\pi + \omega_t^\varepsilon = 1, \quad \omega_t^i \geq 0 \ \forall i \in \{x, \pi, \varepsilon\}.$$

Intuitively, if the observed policy rate is optimal under the true contemporaneous objectives, the implied policy weight vector should make the OPP statistic close to zero: no small perturbation to the policy rate can further improve welfare. Although period-specific estimates are noisy, persistent patterns in the inferred weights over time provide informative evidence about underlying policy priorities.

To be specific, for each year-quarter t, I estimate $\boldsymbol{\omega}_t^*$ by minimizing the dispersion of the OPP statistic around zero, combining forecast draws $\{\mathcal{Y}_t^{0,(m)}\}_{m=1}^M$ with impulse-response draws $\{\mathcal{R}^{0,(d)}\}_{d=1}^D$.

Then, I solve

$$\boldsymbol{\omega}_t^* = \arg\min_{\boldsymbol{\omega}} \mathcal{L}_t^{\text{Huber}}(\boldsymbol{\omega}) = \frac{1}{MD} \sum_{m=1}^{M} \sum_{d=1}^{D} \ell\left(\delta_t^{(m,d)}(\boldsymbol{\omega})\right) \tag{4}$$

where the draw-specific OPP statistic under candidate weight vector $\boldsymbol{\omega}$ is

$$\delta_t^{(m,d)}(\boldsymbol{\omega}) = -\left(\mathcal{R}^{0,(d)\prime} \mathbf{W} \mathcal{R}^{0,(d)}\right)^{-1} \left(\mathcal{R}^{0,(d)\prime} \mathbf{W} \mathcal{Y}_t^{0,(m)}\right), \qquad \mathbf{W} \equiv \text{diag}(\boldsymbol{\omega}) \otimes I_{H+1} \tag{5}$$

I employ a Huber loss function to reduce sensitivity to extreme realizations:

$$\ell(\delta) = \begin{cases} \frac{1}{2}\left(\frac{\delta}{s_t}\right)^2, & \text{if } |\delta| \leq k s_t, \\ k\left|\frac{\delta}{s_t}\right| - \frac{1}{2}k^2, & \text{otherwise,} \end{cases}$$

where $s_t = \text{sd}\Big(\{\delta_t^{(m,d)}(\boldsymbol{\omega})\}_{m,d}\Big)$ and $k = 1.5$.

The optimization is performed over an unconstrained parameterization smoothly mapped

to the unit simplex and solved using the L-BFGS algorithm with multiple random initializations. The resulting sequence $\{\boldsymbol{\omega}_t^*\}_{t=1}^T$ summarizes the evolution of inferred policy priorities over time.

3.2 Time-Invariant policy weight benchmarks

3.2.1 Global-optimal benchmark

I next estimate a single *time-invariant* weight vector $\boldsymbol{\omega}^{\mathrm{GO}}$ that best rationalizes the policy rate over the entire inflation-target period:

$$\boldsymbol{\omega}^{\mathrm{GO}} = \arg\min_{\boldsymbol{\omega}} \frac{1}{T}\sum_{t=1}^{T}\left(\frac{1}{MD}\sum_{m=1}^{M}\sum_{d=1}^{D}\ell\left(\delta_t^{(m,d)}(\boldsymbol{\omega})\right)\right),$$

where $\delta_t^{(m,d)}(\boldsymbol{\omega})$ is defined in Equation 5. In addition to the Huber loss, I include two regularization terms: (i) an ℓ_2 penalty on the unconstrained parameterization, and (ii) a mild entropy penalty on $\boldsymbol{\omega}$ to discourage corner solutions. The optimization is performed using the L-BFGS algorithm with multiple random initializations.

The resulting vector $\boldsymbol{\omega}^{\mathrm{GO}}$ defines the global-optimal benchmark used in subsequent comparisons. Using this benchmark, I construct a time series of OPP statistics as follows. For each period t and each pair of draws (m, d), I compute

$$\delta_t^{\mathrm{GO},(m,d)} = -\left(\mathcal{R}^{0,(d)\prime}\mathbf{W}^{\mathrm{GO}}\mathcal{R}^{0,(d)}\right)^{-1}\left(\mathcal{R}^{0,(d)\prime}\mathbf{W}^{\mathrm{GO}}\mathcal{Y}_t^{0,(m)}\right), \qquad \mathbf{W}^{\mathrm{GO}} \equiv \mathrm{diag}(\boldsymbol{\omega}^{\mathrm{GO}}) \otimes I_{H+1}.$$

I then summarize the cross-draw distribution using the median,

$$\delta_t^{\mathrm{GO,med}} \equiv \mathrm{median}\left\{\delta_t^{\mathrm{GO},(m,d)}\right\}_{m,d},$$

which yields the period-specific OPP series $\left(\delta_t^{\mathrm{GO}}\right)_{t=1}^T$ under the global-optimal benchmark.

3.2.2 Fixed-weight benchmark comparisons

In addition to the global-optimal weight vector discussed above, I evaluate policy rates under two standard fixed-weight benchmarks: (i) an equal-weight benchmark (EQ), $\boldsymbol{\omega}^{\mathrm{EQ}} = \left(\frac{1}{3}, \frac{1}{3}, \frac{1}{3}\right)$, which assigns equal emphasis to output, inflation, and exchange rate stabilization; and (ii) an inflation-target benchmark (IT), $\boldsymbol{\omega}^{\mathrm{IT}} = \left(\frac{1}{2}, \frac{1}{2}, 0\right)$, which mimics a dual-mandate framework by assigning equal weight to output and inflation while placing zero weight on exchange rate stabilization.

For each year-quarter t, I combine forecast-path draws $\{\mathcal{Y}_t^{0,(m)}\}_{m=1}^{M}$ with impulse-response draws $\{\mathcal{R}^{0,(d)}\}_{d=1}^{D}$ to obtain a collection of OPP statistics under each benchmark. Specifically, under the equal-weight benchmark,

$$\delta_t^{\mathrm{EQ},(m,d)} = -\left(\mathcal{R}^{0,(d)\prime}\mathbf{W}^{\mathrm{EQ}}\mathcal{R}^{0,(d)}\right)^{-1}\left(\mathcal{R}^{0,(d)\prime}\mathbf{W}^{\mathrm{EQ}}\mathcal{Y}_t^{0,(m)}\right), \qquad \mathbf{W}^{\mathrm{EQ}} \equiv \mathrm{diag}\left(\tfrac{1}{3}, \tfrac{1}{3}, \tfrac{1}{3}\right) \otimes I_{H+1},$$

and under the inflation-target benchmark,

$$\delta_t^{\mathrm{IT},(m,d)} = -\left(\mathcal{R}^{0,(d)\prime}\mathbf{W}^{\mathrm{IT}}\mathcal{R}^{0,(d)}\right)^{-1}\left(\mathcal{R}^{0,(d)\prime}\mathbf{W}^{\mathrm{IT}}\mathcal{Y}_t^{0,(m)}\right), \qquad \mathbf{W}^{\mathrm{IT}} \equiv \mathrm{diag}\left(\tfrac{1}{2}, \tfrac{1}{2}, 0\right) \otimes I_{H+1}$$

For each year-quarter t, this yields three collections of OPP draws, each with MD elements: $\{\delta_t^{\mathrm{IT},(m,d)}\}_{m,d}$, $\{\delta_t^{\mathrm{EQ},(m,d)}\}_{m,d}$, and $\{\delta_t^{\mathrm{GO},(m,d)}\}_{m,d}$.

For each benchmark $s \in \{\mathrm{IT}, \mathrm{EQ}, \mathrm{GO}\}$, I summarize the cross-draw distribution using the median,

$$\delta_t^{\mathrm{s,med}} \equiv \mathrm{median}\left\{\delta_t^{\mathrm{s,(m,d)}}\right\}_{m,d}.$$

I plot the resulting median series $(\delta_t^{\mathrm{IT,med}})_{t=1}^{T}$, $(\delta_t^{\mathrm{GO,med}})_{t=1}^{T}$, and $(\delta_t^{\mathrm{EQ,med}})_{t=1}^{T}$ in panel (b) of the figures. In addition, because the primary focus of the paper is inflation targeting, I also report uncertainty bands for the IT benchmark by plotting the 68th and 90th percentiles of $\{\delta_t^{\mathrm{IT},(m,d)}\}_{m,d}$ for each t.

3.3 Interpretation

How should we interpret the results? If all weighting schemes imply OPP prescriptions with the same direction and similar magnitude, the conclusion is robust: policy rates are systematically misaligned in that direction. In this case, under all benchmark preferences considered, no specification rationalizes the observed policy rate as optimal, implying that there remains scope for welfare-improving policy adjustment. Understanding the institutional or political motivations behind such episodes may require additional qualitative evidence, such as central bank communications or official policy statements (e.g., concerns about financial stability).

By contrast, if the inflation-target benchmark yields OPP values close to zero while alternative benchmarks imply significant deviations, this reveals the underlying trade-offs faced by policymakers. For example, if the equal-weight benchmark prescribes tightening while the inflation-target benchmark implies no deviation, this indicates that the central bank places relatively greater weight on inflation stabilization than on output or exchange-rate stabilization. Comparisons across benchmarks therefore help uncover the implicit policy priorities that rationalize observed decisions under one preference structure but not under others, especially during financial crises.

4 Data

4.1 Macroeconomic variables

To estimate impulse responses, I use quarterly seasonally adjusted real GDP growth from the IMF's International Financial Statistics (IFS), supplemented with the Macro-financial dataset of Camous, Monnet and Puy (2025). Quarterly consumer price indices are also drawn from the IFS. Since many CPI series are not seasonally adjusted, I deseasonalize them using the X-13 method. Effective exchange rate indices are obtained from the IFS as well.[7] All macroeconomic series are cross-checked against the comprehensive dataset of Obstfeld and Zhou (2022) to ensure consistency.

The most challenging aspect of data construction concerns monetary policy rates. Many central banks in emerging markets did not operate with a clearly defined policy rate until relatively recently, and operational instruments vary substantially across countries and over time. Unlike the Federal Funds rate—an unsecured interbank overnight rate—Table 2 shows that policy rates in emerging markets often correspond to collateralized short-term rates with maturities ranging from overnight to several weeks. In some cases, the reported "policy rate" reflects the central bank's discount rate rather than the marginal rate targeted through open market operations.

Institutional changes further complicate measurement. Several central banks have altered their operating monetary instruments over time, and episodes of high inflation and currency redenomination can mechanically distort reported interest rates.[8] These features introduce substantial noise into cross-country comparisons.

To mitigate these issues, I restrict the impulse response estimation to periods in which each country operated with a single, clearly defined policy rate, as documented in Table

[7] Bilateral exchange rates against the U.S. dollar are often excessively volatile. I therefore rely on trade-weighted exchange rates, which provide smoother and more informative measures of external conditions.

[8] For example, Brazil's currency redenominations in the early 1990s reduced published policy rates by several orders of magnitude in the BIS series.

2. These periods typically coincide with the formal adoption of inflation-targeting regimes. This restriction also avoids distortions arising from high-inflation episodes and currency redenomination.

4.2 Expected deviations from the forecast path

The OPP statistic requires expected forecast paths $\mathcal{Y}_t^0 \in \mathbb{R}^{N(H+1)}$ of macroeconomic variables. I construct these using professional forecasts from the Economist Intelligence Unit (EIU) for real GDP growth, inflation, and currency depreciation. As an independent organization, the EIU provides long-horizon forecasts for a broad set of countries—many extending back to 1994—using a consistent methodology that facilitates cross-country comparability.[9]

These forecast paths vary over time because the EIU updates forecasts in each publication, while the impulse response estimates remain fixed over the sample.

The publication frequency of EIU reports evolves over time. Earlier issues are typically quarterly, while reports become monthly in the early 2000s. For consistency, I use quarterly forecasts in earlier periods and select forecasts from the January, April, July, and October issues when monthly publications are available.

EIU forecasts are reported as point forecasts for end-of-calendar-year outcomes up to five years ahead. As a result, each issue provides a term structure of expectations at unevenly spaced horizons. For example, the January issue contains forecasts approximately 11, 23, 35, 47, and 59 months ahead, while the April issue corresponds to roughly 8, 20, 32, 44, and 56 months ahead. Later issues follow the same structure with progressively shorter effective horizons.

To align these forecasts with the quarterly horizons used in the impulse response analysis, I linearly interpolate forecast paths across horizons at the monthly frequency and

[9]Central banks' internal forecasts may contain private information unavailable to professional forecasters, and analyses based on real-time policymaker data can differ systematically from those using ex post revised data (Romer and Romer, 2000; Orphanides, 2001). However, consistent historical central-bank forecasts are largely unavailable for emerging markets. Moreover, even when official projections exist, they may be subject to political pressures that bias reported expectations.

then retain values closest to 12, 24, 36, 48, and 60 months ahead (corresponding to 4, 8, 12, 16, and 20 quarters). This procedure yields consistent forecast paths up to 20 quarters ahead in every period, despite differences in publication timing. I then follow the procedure detailed in Section 2.3 to construct posterior draws of forecast paths $\{\mathcal{Y}_t^{0,(m)}\}_{m=1}^{M}$.

5 Main Results and Discussions

Figures 1–12 summarize the main results for each emerging market. Each country is evaluated using a common two-panel structure. Visual inspection reveals systematic patterns across country groups sharing similar monetary policy traditions, so the discussion is organized by economically meaningful country groups rather than alphabetically.

Panels (a) report time-varying revealed policy priorities—i.e., the policy weight vectors that minimize the OPP deviation from zero in each year-quarter. These series are informative about whether the inflation weight is economically meaningful and whether it remains stable over time, providing an intuitive and transparent indicator of inflation-target credibility.

Panels (b) compare OPP statistics across alternative rule-based benchmarks, with the inflation-target benchmark—featuring only the inflation-output tradeoff—as the primary reference. Conditional on EIU forecasts approximating policymakers' information sets, the OPP framework provides a disciplined way to evaluate whether observed monetary policy responses during crises were insufficient, excessive, or mistimed. Comparisons with the equal-weight and global-optimal benchmarks quantify both the direction and the magnitude of deviations from the inflation-target benchmark.

5.1 Asian emerging markets: stable inflation emphasis with pronounced crisis-driven deviations

I begin with four Asian emerging markets: South Korea, Thailand, Indonesia, and the Philippines. Prior to the 2000s, these economies exhibited limited monetary autonomy under de facto pegged exchange rate regimes supporting export-led growth. Following the 1997 Asian Financial Crisis, reserve accumulation and institutional reforms expanded monetary policy flexibility, allowing the inflation-target adoption without fully compromising exchange rate stability.

Panels (a) of Figures 1–2 show substantial cross-country heterogeneity in revealed

policy priorities. South Korea and Indonesia place relatively little weight on exchange rate stabilization—global-optimal weights are approximately $(0.50, 0.44, 0.06)$ and $(0.51, 0.36, 0.13)$ respectively. Moreover, their time-varying revealed policy priorities become more stable over time, converging toward a balanced inflation-output trade-off, consistent with the maturation of inflation-target regimes and comparatively stronger democratic institutions and central bank independence.

In contrast, Thailand and the Philippines retain substantially higher revealed emphasis on exchange rate stabilization. Their global-optimal weights, $(0.31, 0.34, 0.35)$ and $(0.33, 0.35, 0.32)$ respectively, lie close to the equal-weight benchmark. This pattern plausibly reflects institutional and structural differences. Thailand's monetary framework has been shaped by repeated political disruptions and higher export exposure. The Philippine economy, in turn, is heavily dependent on foreign remittances, implying that exchange rate movements carry salient distributional and political consequences.

Crisis episodes generate pronounced temporary deviations in policy trade-offs across all four economies. Panels (a) of Figures 1 and 2 show that during the 1997 Asian Financial Crisis, South Korea and Indonesia experienced sharp spikes in exchange rate weight followed by immediate declines after the pegs broke. In the post-crisis period, output weights temporarily increased before reverting back toward inflation. Similar crisis-driven reweighting appears, to varying degrees, in Thailand and the Philippines. Overall, crisis episodes and their subsequent economic downturns are consistently associated with elevated concern for real activity or exchange rate stability.

Panels (b) of Figures 1–4 translate constant-weight benchmarks into counterfactual policy prescriptions. For South Korea, Panel (b) of Figure 1 indicates that during the 2008 Global Financial Crisis all benchmarks imply sizable easing—roughly 150–250 basis points—suggesting that the policy rate could have responded more aggressively. In contrast, during the 1997 Asian Financial Crisis, the inflation-target and global-optimal benchmarks prescribe monetary easing of 100–150 basis points, whereas the equal-weight benchmark

suggests tightening of around 150 basis points. This divergence highlights the underlying policy dilemma between anchoring inflation expectations versus stabilizing output growth and the exchange rate.

Indonesia, Thailand, and the Philippines all display analogous tensions. In Indonesia (Panel (b) of Figure 2), the equal-weight benchmark prescribes a 150 basis point tightening during the 1997 Asian Financial Crisis, while inflation-target and global-optimal benchmarks suggest smaller adjustments; all benchmarks subsequently converge toward easing of about 50 basis points immediately after the crisis. Thailand (Panel (b) of Figure 3) occupies an intermediate position: equal-weight and global-optimal benchmarks both recommend monetary tightening of about 50 basis points during the 1997 Asian Financial Crisis but not during the 2008 Global Financial Crisis, whereas the inflation-target benchmark prescribes modest easing (about 25 basis points) in both episodes. For the Philippines (Panel (b) of Figure 4), benchmark disagreement during crisis periods—equal-weight and global-optimal benchmarks suggest monetary tightening of about 50–100 basis points—similarly reflects competing stabilization objectives.

Overall, heterogeneity in monetary policy prescriptions across countries and crisis episodes reflects differences in institutional credibility and external vulnerability—precisely the dimensions that the OPP framework is designed to capture. These findings are consistent with Fraga, Goldfajn and Minella (2003)'s argument that emerging markets' constraints on credbility and external shocks (e.g., sudden stop) necessitate flexible inflation-target implementations that balance multiple stabilization objectives.

5.2 Historically high-inflation Latin American economies: convergence toward inflation dominance

The second country group consists of Brazil, Chile, Colombia, Peru, and Mexico—emerging economies with histories of chronic high inflation or hyperinflation. These cases provide a natural laboratory for examining how inflation-target adoption reshaped monetary policy

priorities during the transition to low-inflation regimes.

Brazil exhibits the sharpest regime shift. Panel (a) of Figure 5 shows that prior to inflation-target adoption, policy priorities fluctuated substantially and placed limited emphasis on inflation stabilization, with greater attention to output and exchange rate. This pattern is consistent with heightened concerns about regional contagion during Argentina's 2001 default episode. Following the consolidation of the inflation-target regime in the mid-2000s, the inflation weight rises sharply and becomes persistently dominant. The global-optimal benchmark $(0.56, 0.33, 0.11)$ confirms this post-crisis inflation dominance and the stabilization of policy priorities.

Mexico displays a more gradual but similarly sharp and persistent transition. Panel (a) of Figure 6 indicates that before the formal adoption of the inflation-target framework in 2001, revealed policy priorities placed little emphasis on inflation stabilization, consistent with the post-Tequila Crisis environment. Afterward, the inflation weight rises sharply and remains elevated throughout the sample period. The global-optimal benchmark $(0.32, 0.62, 0.06)$ suggests near-exclusive emphasis on inflation-output stabilization, with minimal concern for exchange-rate objectives.

Chile follows a comparable but more balanced pattern. Panel (a) of Figure 7 shows that after formal inflation targeting in 1999, inflation stabilization becomes the dominant objective, though exchange-rate and output considerations remain non-negligible. Temporary shifts toward output stabilization emerge during major downturns, most notably the 2008 Global Financial Crisis. The global-optimal benchmark $(0.44, 0.31, 0.25)$ reflects this more balanced but still inflation-centered regime.

Colombia also exhibits sustained inflation dominance following the inflation-target adoption in 1999. Panel (a) of Figure 8 shows that post-adoption fluctuations in policy weights primarily reflect trade-offs between output and exchange rate, while the inflation weight remains consistently high and stable. The global-optimal benchmark $(0.6, 0.36, 0.04)$ confirms limited concern for exchange rate stabilization. Peru, in contrast, stands out as an

exception: Panel (a) of Figure 9 shows persistently elevated exchange rate weights even after inflation targeting, indicating continued emphasis on external stability.

Panels (b) of Figures 5–9 reveal greater volatility in monetary prescriptions than in the Asian group of Section 5.1. For Brazil, Panel (b) of Figure 5 shows that equal-weight and global-optimal benchmarks often prescribe tighter monetary policy during major stress episodes, including the early-2000s turbulence, the 2008 Global Financial Crisis, and the 2015 political-fiscal crisis, while the inflation-target benchmark implies comparatively muted adjustments. This divergence underscores the extent to which Brazil's realized policy appears aligned with inflation emphasis rather than broader stabilization objectives.

Chile and Peru exhibit smaller and smoother OPP deviations. Panel (b) of Figure 7 shows that in Chile, disagreement across benchmarks is modest and largely confined to crisis periods. For example, the equal-weight benchmark prescribes a mild 50 basis point tightening during the 2008 Global Financial Crisis, while the inflation-target benchmark suggests the opposite. Panel (b) of Figure 9, in contrast, shows consistent benchmark prescriptions of mild tightening of policy rates by about 50–100 basis points during the early inflation-target adoption period, the 2008 Global Financial Crisis, and the COVID-19 pandemic.

Mexico shows the most volatile OPP statistics in this country group. During the 1994–2000 currency crisis period, all benchmarks unanimously suggest substantial tightening, often exceeding 100–250 basis points. After the inflation-target adoption, the OPP deviations under the inflation-target benchmark become smaller and more stable, while equal-weight and global-optimal benchmarks remain considerably more volatile. This pattern suggests that the Bank of Mexico has consistently prioritized inflation stabilization relative to alternative objectives.

Overall, the Latin American evidence illustrates how inflation-target regimes facilitated rapid and durable convergence toward low and stable inflation environments. Even in economies with severe historical inflation episodes, the OPP framework shows a gradual stabilization of revealed policy priorities toward inflation dominance, consistent with successful

re-anchoring of inflation expectations and institutional credibility.

5.3 Extreme performers and underperformers

This section highlights three notable examples for comparing inflation-target credibility: South Africa as a strong performer, Turkey as a clear underperformer, and Israel as an intermediate case.

South Africa stands out as a benchmark case of credible inflation targeting. Panel (a) of Figure 10 shows a persistently high and stable inflation weight, with limited emphasis on exchange rate stabilization. The global-optimal benchmark $(0.39, 0.54, 0.07)$ confirms this structure. Panel (b) further shows that the inflation-target OPP statistic remains tightly centered around zero, while the equal-weight benchmark occasionally prescribes modest tightening of 50–100 basis points. Together, these patterns indicate that South Africa consistently prioritizes inflation stabilization over competing objectives and exhibits close alignment with a credible inflation-target regime.

Turkey, by contrast, represents the clearest breakdown of inflation-target credibility in the sample. Panel (a) of Figure 12 shows persistent dominance of output stabilization with little sustained weight on inflation. Panel (b) displays large—but consistently aligned tightening prescriptions across all three benchmarks—OPP deviations throughout the sample. During 1994–2005, all benchmarks prescribe aggressive monetary tightening, often exceeding 250 basis points. Although OPP deviations appear more stable between 2005 and 2020, most benchmarks continue to imply that policy rates should have been higher by roughly 50 basis points. After 2020, deviations rise sharply again across all benchmarks, with prescriptions frequently exceeding 100–250 basis points. This pattern is consistent with a collapse of inflation-target credibility rather than simple mis-calibration of policy trade-offs, in line with well-documented political interference in monetary policy since the 2020s.

Israel occupies an intermediate position. Panel (a) of Figure 11 shows that inflation generally receives substantial weight over the sample, consistent with the global-optimal

benchmark $(0.24, 0.48, 0.28)$. At the same time, policy priorities exhibit greater time variation than in South Africa, with occasional shifts toward output stabilization, most noticeably since the 2020s. Panel (b) shows OPP deviations that are larger and more volatile than in South Africa but far smaller than in Turkey. During recent periods of heightened external and geopolitical stress, the inflation-target benchmark typically prescribes modest tightening of around 50 basis points, broadly consistent with the suggestions from other benchmarks. Overall, Israel appears to maintain inflation-target credibility but faces sharper short-run trade-offs due to geopolitical conflicts than highly stable benchmark cases.

Taken together, these cases underscore the central role of institutional stability for inflation-target credibility. Countries such as South Africa, where revealed policy priorities are stable and OPP deviations remain small, exhibit behavior consistent with the inflation-target framework. In contrast, Turkey illustrates how persistent political interference and shifting policy priorities can generate large and systematic deviations from inflation-target benchmarks. Intermediate cases such as Israel highlight the constraints faced by small open economies often exposed to external shocks and geopolitical risk, where maintaining inflation-target credibility may require temporary departures from strict rule-based policy.

5.4 Cross-country lessons

The above results yield three central lessons. First, time-varying revealed policy priorities provide a transparent and informative measure of evolving monetary policy priorities. Among successful inflation-target regimes—including Brazil, Chile, Colombia, Indonesia, Mexico, South Korea, and South Africa—the inflation-target adoption coincides with a pronounced and persistent increase in the inflation weight, alongside gradual convergence toward lower and more stable inflation observed over the past two decades. Countries such as Brazil, Colombia, and South Africa appear to maintain strict adherence to inflation dominance throughout, while others—such as Chile and Indonesia—nonetheless exhibit temporary reallocations toward output stabilization; however, those with historically stable inflation weights tend

to revert more quickly to inflation primacy after shocks. Both patterns are consistent with credible and internally coherent policy frameworks.

Second, the OPP statistic provides a quantitative measure of policy performance. Across most countries, alternative benchmarks—inflation-target, equal-weight, and global-optimal—deliver broadly similar directional policy prescriptions despite differences in magnitude. Extreme cases illustrate this contrast sharply. For Turkey, all benchmarks consistently suggest aggressive tightening, indicating severe credibility failures. For strong performers such as South Korea, the OPP statistics instead highlight missed opportunities for more timely and decisive easing during the 2008 Global Financial Crisis.

Third, cross-country heterogeneity reflects differences in institutional development and approaches to crisis management. Latin American economies with histories of high inflation exhibit the sharpest and most durable transitions toward inflation dominance following the inflation-target adoption. By contrast, countries with weaker institutional commitment—most notably Turkey—continue to display unstable policy weights on inflation and large OPP deviations despite formal regime adoption.

Overall, credible inflation-target regimes are characterized by convergence toward stable inflation dominance and declining OPP deviations over time. South Korea, Brazil, Chile, and Mexico exhibit this pattern. At the same time, small open economies such as Israel and Thailand face additional constraints from geopolitical risk and external shocks, leading to temporary departures from the strict inflation-target benchmark. Persistent OPP deviations across all benchmarks in countries such as Turkey, however, underscore the limits of formal regime adoption in the absence of institutional discipline.

6 Concluding Remarks

High inflation imposes substantial economic costs by distorting price signals, redistributing wealth arbitrarily, and weakening expectation formation—an essential channel through which both conventional and unconventional monetary policies operate. In emerging markets, where expectations are often fragile and credibility hard-won, maintaining a consistent and transparent inflation-target framework is therefore central to macroeconomic stabilization.

This paper evaluates whether central banks in emerging markets credibly adhere to their stated inflation-target frameworks. While credibility is widely viewed as central to anchoring inflation expectations, many emerging markets have long histories of inflation volatility and repeated episodes of macroeconomic instability. This raises the question of whether formal inflation-target commitments meaningfully discipline monetary policy in practice.

To address this question, I develop an empirical framework based on optimal policy perturbation (OPP) statistics to assess monetary policy credibility. The analysis yields three main findings:

First, the revealed-preference estimates show that many emerging markets have placed increasing and more stable weight on inflation stabilization since the early 2000s. This pattern is especially pronounced in countries with histories of chronic or high inflation, such as Brazil, Chile, and Mexico. The evolution of implied policy weights suggests a structural reorientation of monetary policy toward price stability, consistent with a strengthening of inflation-target credibility over time.

Second, deviations from inflation-focused behavior are concentrated around crisis episodes. During severe downturns, central banks often shift weight temporarily toward output stabilization, reflecting the inherent trade-offs of crisis management in small open economies. Importantly, however, the optimal direction and magnitude of policy adjustment vary substantially across countries. For example, during the 2008 Global Financial Crisis,

the OPP framework suggests that the Bank of Korea should have eased more aggressively, whereas policy in Peru should have been modestly tighter. These contrasts underscore the role of country-specific institutional features, external vulnerabilities, and inflation dynamics in shaping optimal monetary policy responses.

Third, the framework identifies clear cases of weak or deteriorating credibility. Most notably, Turkey exhibits persistent and large deviations from the inflation-target-consistent policy path, even under identifying assumptions that are maximally favorable to the central bank. This evidence suggests that the formal adoption of inflation targeting is insufficient in the absence of institutional discipline and sustained political commitment.

Overall, the evidence is cautiously optimistic. Since the turn of the millennium, many central banks in emerging markets have increasingly prioritized inflation stabilization, helping to rationalize the sustained decline in inflation observed across these economies. While temporary departures occur during crises—particularly in small open economies exposed to financial or geopolitical shocks—most central banks subsequently revert to inflation-dominant policy behavior. This pattern points to a gradual strengthening of monetary credibility and supports a favorable outlook for the long-run effectiveness of inflation-target frameworks in emerging markets.

Table 1: Inflation-target framework and inflation outcomes in emerging markets

	Target framework			Inflation outcomes (2024, YoY)		
Country	Start	Type	Current level(s)	Actual	Forecast (1yr)	Forecast (avg)
(1)	(2)	(3)	(4)	(5)	(6)	(7)
BRA	1999	Band	3% ± 1.5% pt	4.3%	3.8%	3.6%
CHL	1999	Point	3%	4.2%	4.1%	3.1%
COL	1999	Point	3%	6.4%	4.2%	3.2%
IDN	2005	Band	2.5% ± 1% pt	2.2%	2.5%	2.9%
ISR	1992	Band	1%–3%	3.0%	3.1%	1.9%
KOR	1997	Point	2%	2.3%	1.8%	1.7%
MEX	2001	Band	3% ± 1% pt	4.6%	3.9%	3.3%
PER	2002	Point	2%	2.0%	2.3%	2.4%
PHL	2002	Band	2%–4%	3.2%	2.6%	3.0%
THA†	2000	Band	1%–3%	0.5%	2.2%	2.1%
TUR†	2006	Band	5% ± 2% pt	49.4%	28.5%	18.0%
ZAF	2000	Point	4.5%	4.3%	4.2%	4.2%

Notes: This table summarizes the recent implementation of inflation-target frameworks across 12 emerging markets. Information on the official adoption year, target type, and current target level(s) is obtained from central Banks' official websites. *Current level(s)* refers to the most up-to-date announced inflation target, recognizing that many central Banks operate under flexible inflation-target regimes in which target bands or point targets are revised and announced several years in advance (for example, the Philippines typically announces revisions two years ahead). *Actual* inflation is measured as the 2024 average of quarterly year-on-year log changes in the consumer price index (CPI) using data from the IMF International Financial Statistics. Inflation expectations are taken from the Economist Intelligence Unit (EIU). *Forecast (1yr)* reports the EIU forecast for calendar-year CPI inflation in 2025, while *Forecast (avg)* reports the average of EIU forecasts for calendar-year CPI inflation over the 2025–2029 period, capturing medium-run inflation expectations. †: For Thailand and Turkey, actual inflation is computed using the latest available CPI data in 2024 (2023Q4–2024Q3). Except for Turkey, EIU forecasts are taken from the October 2024 EIU country forecast reports; for Turkey, forecasts are from the July 2024 report due to data availability.

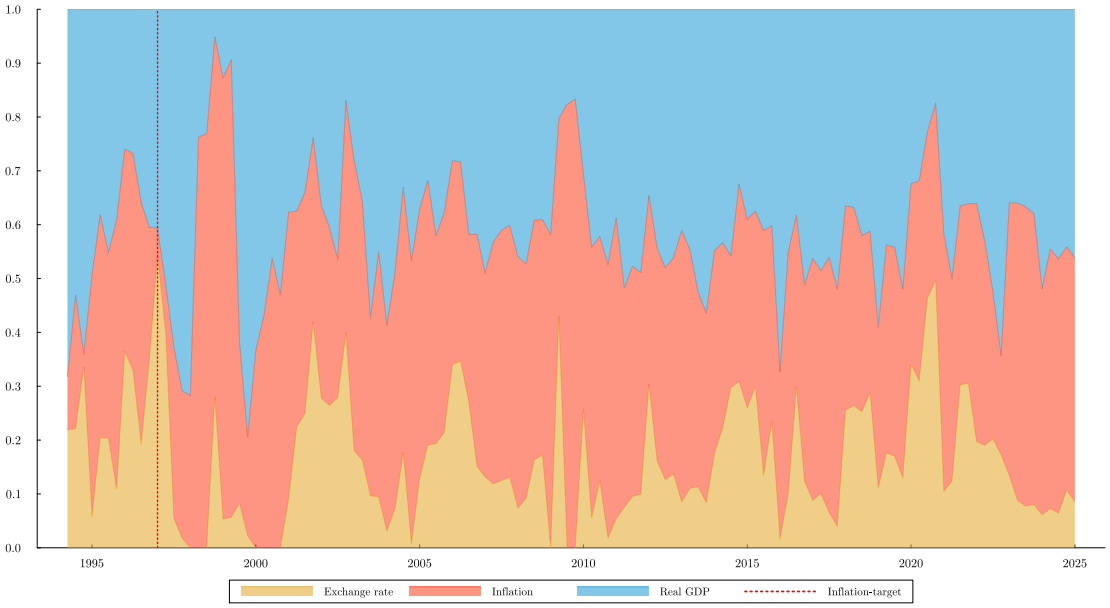
Table 2: Monetary instruments under inflation-target in emerging markets

						Stabilization Objectives		
Country	Policy Instrument	Target Facility	Maturity	Secured	Policy Rate (%)	Growth	Price	EXR
(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)	(9)
BRA	SELIC Rate	Interbank	O/N	✓	12.4 (5.0)		✓	
CHL	MP Rate	Interbank	O/N		4.2 (2.4)		✓	
COL	MP Rate	Interbank	O/N		6.6 (3.3)	✓	✓	
IDN	BI Rate	Central Bank	7-day	✓	6.6 (2.2)		✓	✓
ISR	SHIR Rate	Interbank	O/N		4.9 (4.8)		✓	
KOR	BOK Base Rate	Central Bank	7-day	✓	2.9 (1.4)		✓	
MEX	Target Rate	Interbank	O/N		6.1 (2.5)		✓	
PER	Reference Rate	Interbank	O/N		3.7 (1.7)		✓	
PHL	Reverse Repo Rate	Central Bank	Pre-specified	✓	4.7 (2.0)		✓	
THA	1-day Repo Rate	Central Bank	O/N	✓	2.1 (1.1)	✓		
TUR	7-day Repo Rate	Central Bank	7-day	✓	13.4 (11.3)		✓	
ZAF	Repo Rate	"Tiered-floor System"	O/N	✓	7.2 (2.3)	✓	✓	

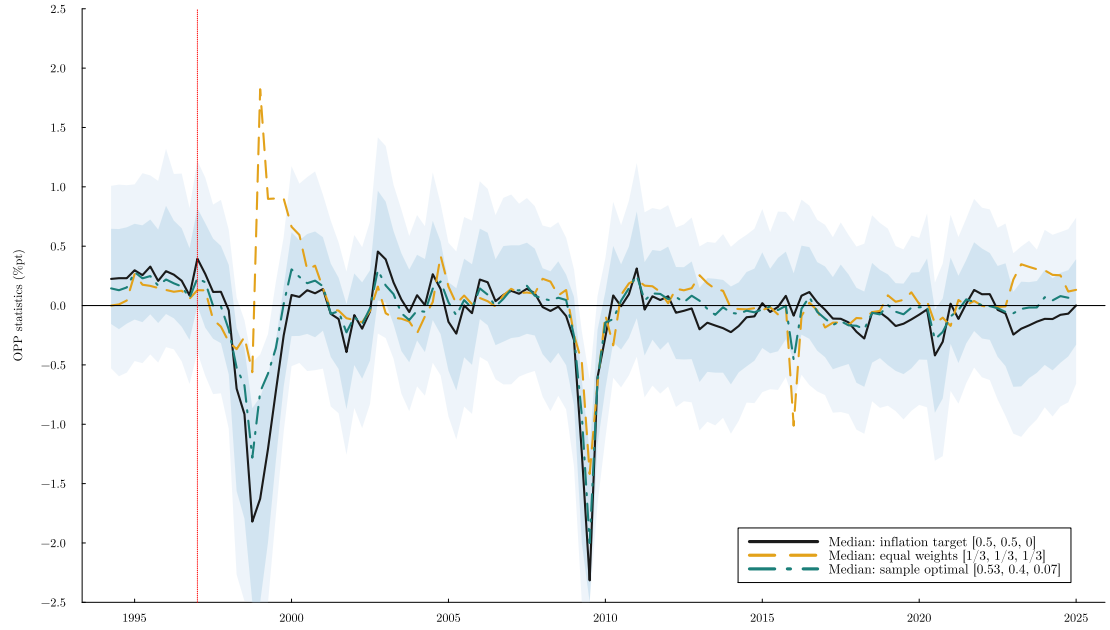
Notes: This table summarizes heterogeneity in the operational implementation of monetary policy across emerging markets, focusing on the target facility, maturity, and collateralization of policy instruments, relative to the Federal Funds Rate, which is defined as the target overnight unsecured interbank borrowing rate in the United States. *Policy Instrument* reports the official name of each central bank's monetary policy target rate. *Target Facility* indicates whether monetary policy implementation operates through the interbank market (i.e., transactions among commercial banks via open market operations) or directly through borrowing from or lending to the central bank (e.g., repurchase or reverse repurchase facilities). *Maturity* refers to the tenor of the instrument targeted by the central bank, with "O/N" denoting overnight maturity. *Secured* indicates whether transactions are collateralized by government securities. *Policy Rate* (%) reports the mean policy rate over the inflation-target period, with the standard deviation shown in parentheses; sample periods vary across countries depending on the timing of inflation-target adoption and data availability. Columns (7)–(9) summarize central banks stated macroeconomic policy objectives, based on official mission statements published on their official websites, indicating whether output stabilization, price stability, or exchange rate considerations are explicitly mentioned. All information is obtained from the most recent official central bank websites.

Figure 1: South Korea—Revealed policy priorities and OPP-based policy evaluation

(a) Time-varying policy weights that rationalize observed policy rate



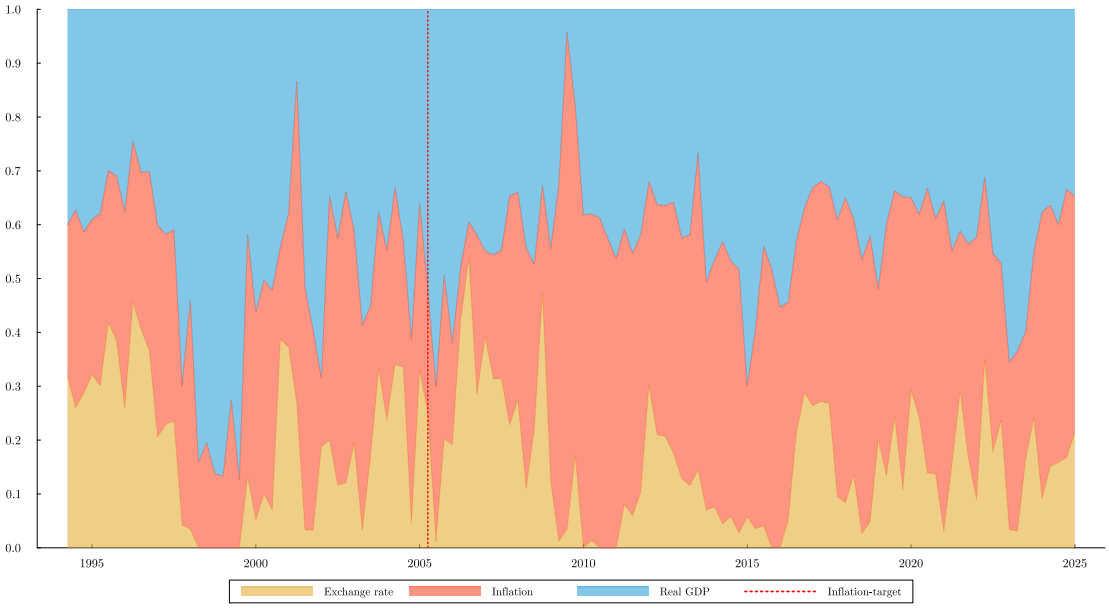
(b) OPP statistics across different constant-weight benchmarks



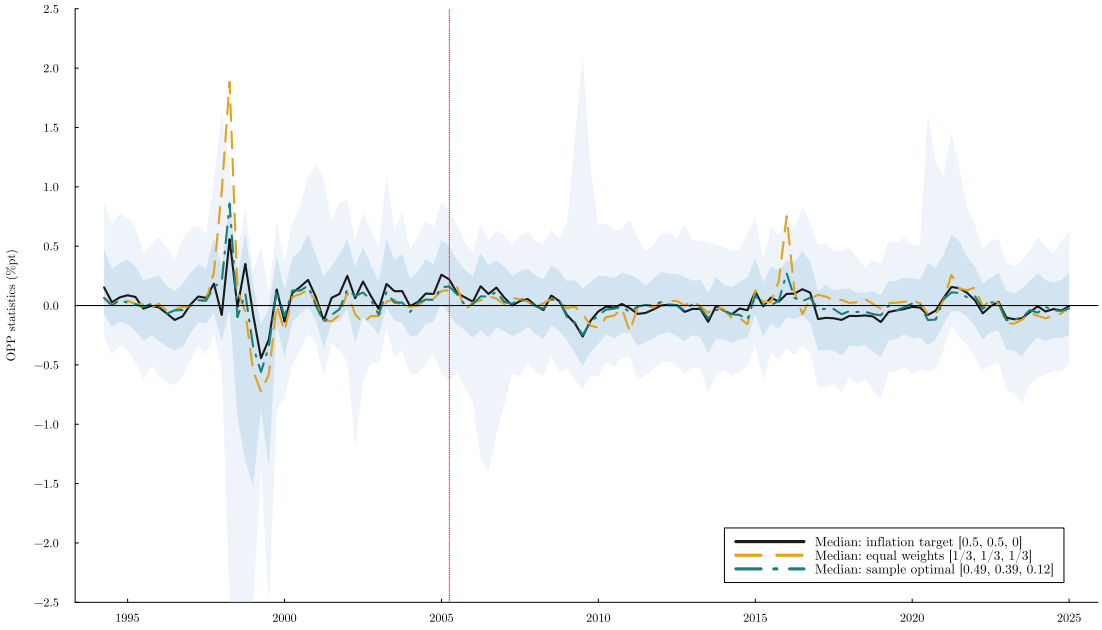
Notes: This figure evaluates the credibility of inflation-target monetary policy in South Korea. Panel (a) reports the period-specific optimal policy weights—interpreted as revealed preferences over policy trade-offs—that minimize the OPP deviation from zero in each year-quarter. Panel (b) plots the median OPP statistic under the inflation-target benchmark as well as its 68% and 90% percentile bands. For comparison, the median OPP series under the equal-weight benchmark and the global-optimal benchmark are also shown. The vertical red dotted line marks the official adoption of inflation-target in South Korea.

Figure 2: Indonesia—Revealed policy priorities and OPP-based policy evaluation

(a) Time-varying policy weights that rationalize observed policy rate



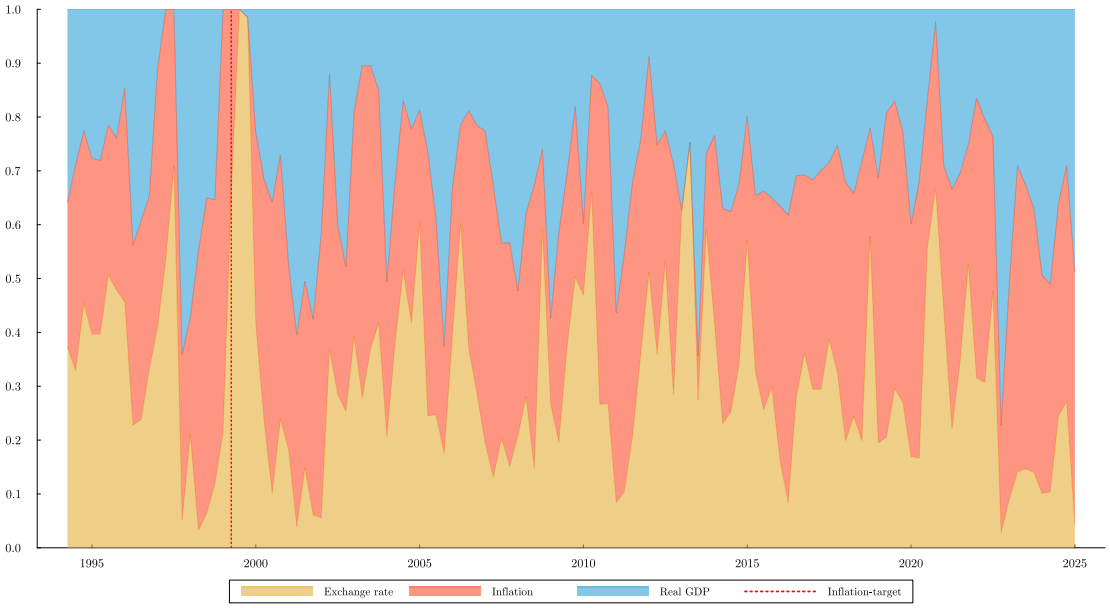
(b) OPP statistics across different constant-weight benchmarks



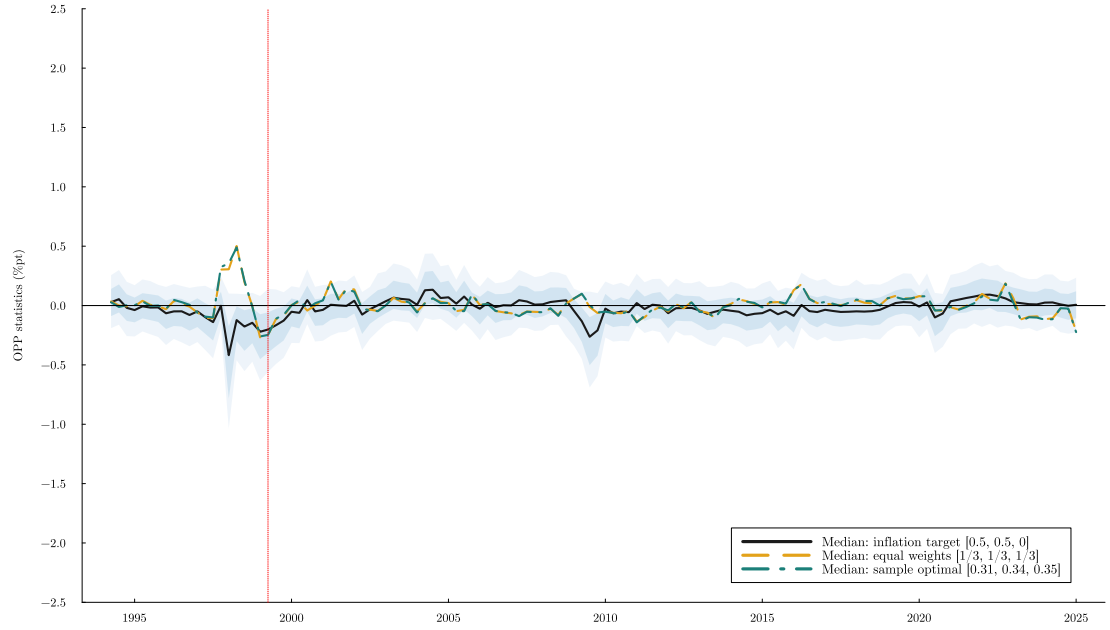
Notes: This figure evaluates the credibility of inflation-target monetary policy in Indonesia. Panel (a) reports the period-specific optimal policy weights—interpreted as revealed preferences over policy trade-offs—that minimize the OPP deviation from zero in each year-quarter. Panel (b) plots the median OPP statistic under the inflation-target benchmark as well as its 68% and 90% percentile bands. For comparison, the median OPP series under the equal-weight benchmark and the global-optimal benchmark are also shown. The vertical red dotted line marks the official adoption of inflation-target in Indonesia.

Figure 3: Thailand—Revealed policy priorities and OPP-based policy evaluation

(a) Time-varying policy weights that rationalize observed policy rate



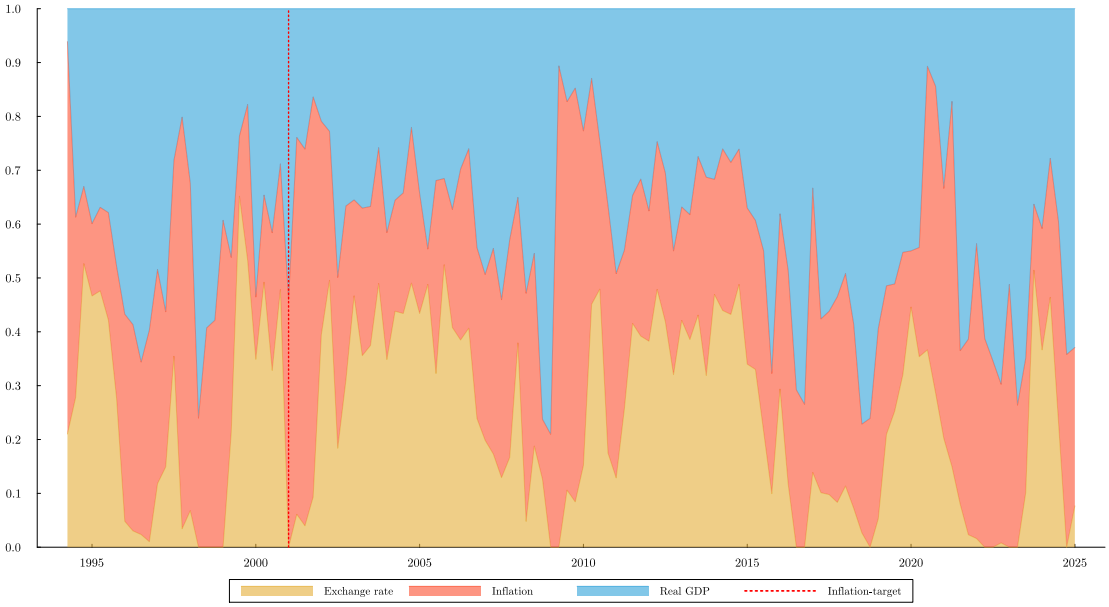
(b) OPP statistics across different constant-weight benchmarks



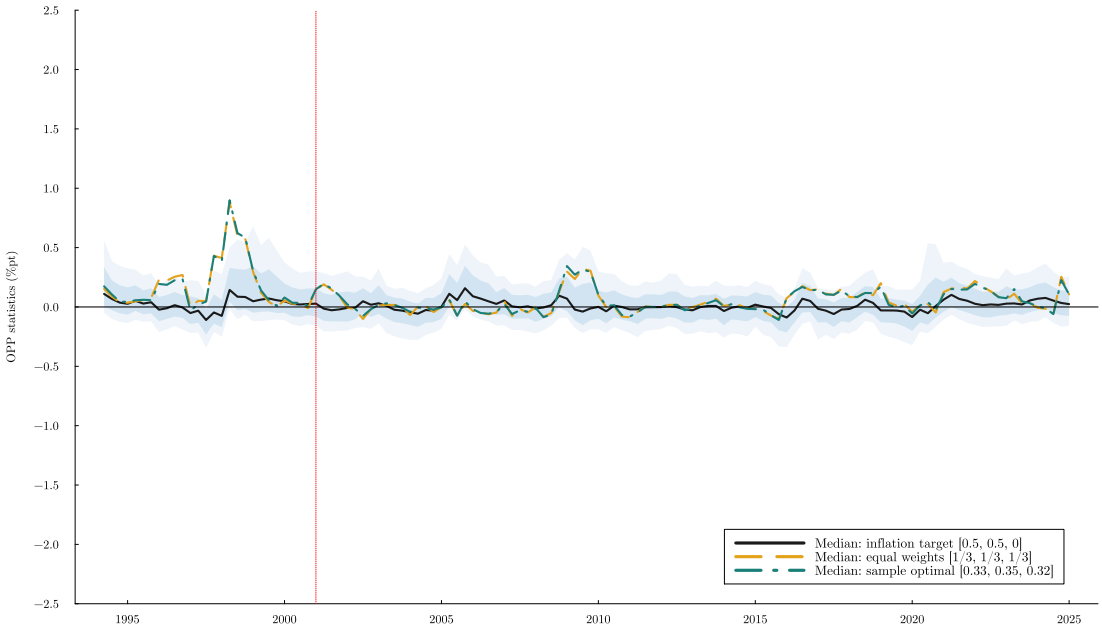
Notes: This figure evaluates the credibility of inflation-target monetary policy in Thailand. Panel (a) reports the period-specific optimal policy weights—interpreted as revealed preferences over policy trade-offs—that minimize the OPP deviation from zero in each year-quarter. Panel (b) plots the median OPP statistic under the inflation-target benchmark as well as its 68% and 90% percentile bands. For comparison, the median OPP series under the equal-weight benchmark and the global-optimal benchmark are also shown. The vertical red dotted line marks the official adoption of inflation-target in Thailand.

Figure 4: The Philippines—Revealed policy priorities and OPP-based policy evaluation

(a) Time-varying policy weights that rationalize observed policy rate



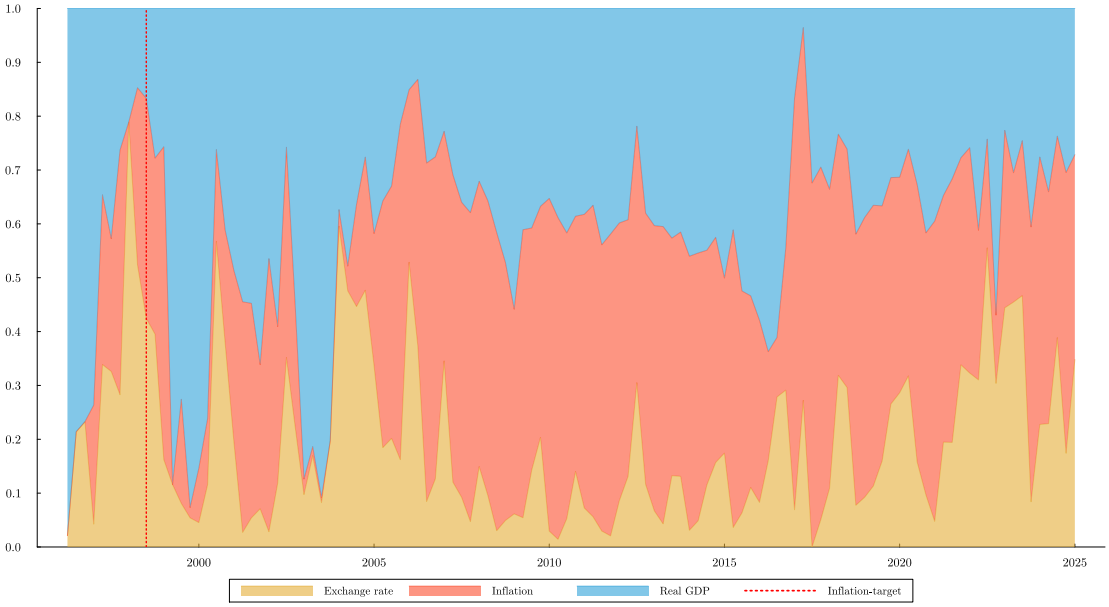
(b) OPP statistics across different constant-weight benchmarks



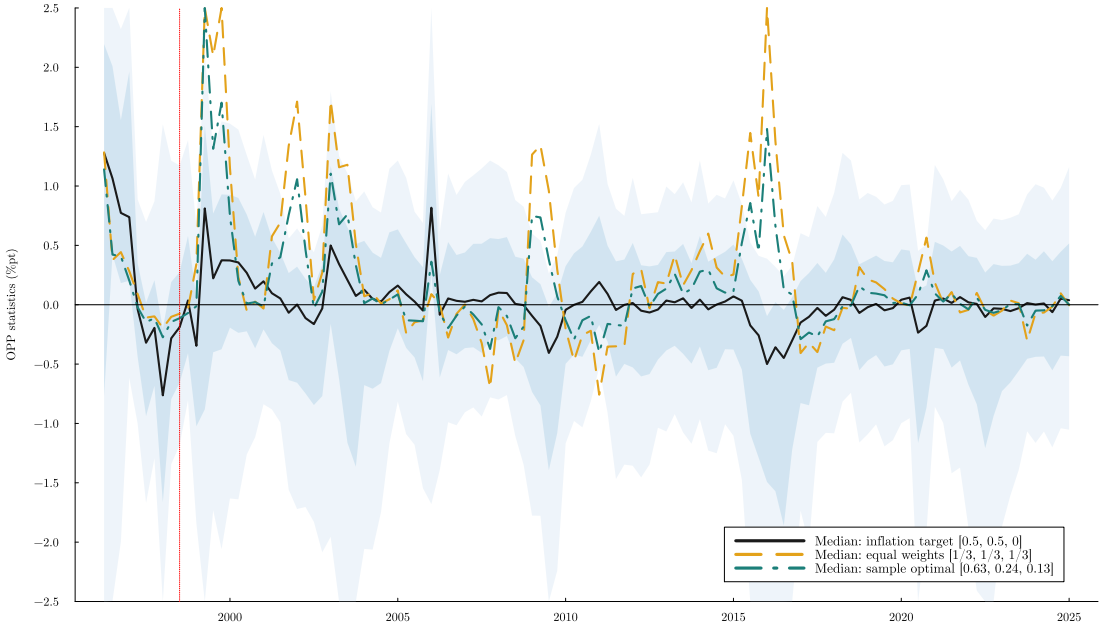
Notes: This figure evaluates the credibility of inflation-target monetary policy in The Philippines. Panel (a) reports the period-specific optimal policy weights—interpreted as revealed preferences over policy trade-offs—that minimize the OPP deviation from zero in each year-quarter. Panel (b) plots the median OPP statistic under the inflation-target benchmark as well as its 68% and 90% percentile bands. For comparison, the median OPP series under the equal-weight benchmark and the global-optimal benchmark are also shown. The vertical red dotted line marks the official adoption of inflation-target in The Philippines.

Figure 5: Brazil—Revealed policy priorities and OPP-based policy evaluation

(a) Time-varying policy weights that rationalize observed policy rate



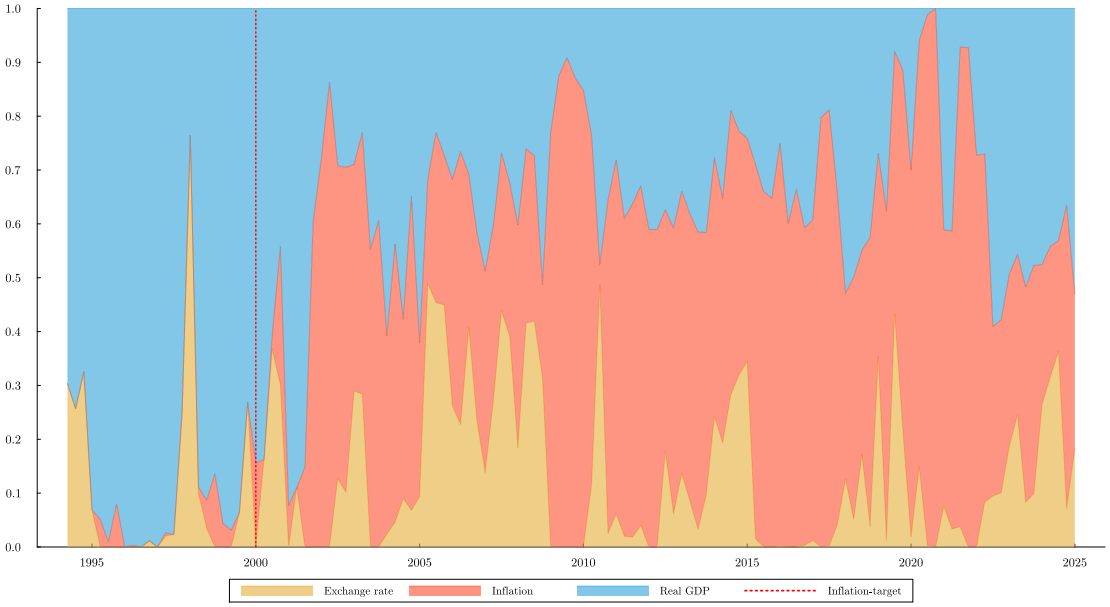
(b) OPP statistics across different constant-weight benchmarks



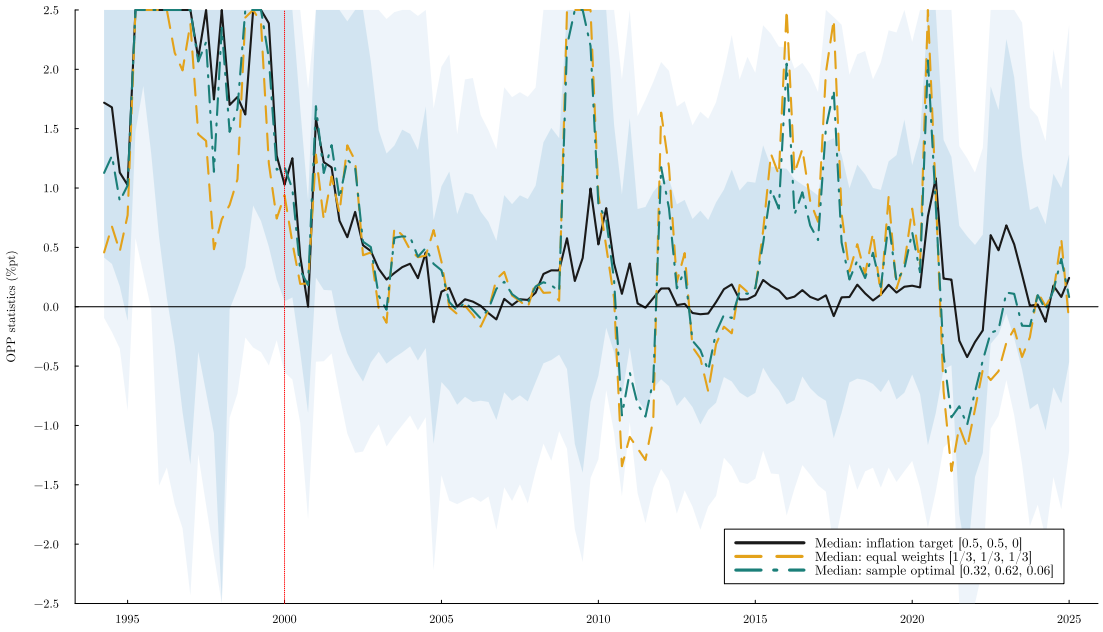
Notes: This figure evaluates the credibility of inflation-target monetary policy in Brazil. Panel (a) reports the period-specific optimal policy weights—interpreted as revealed preferences over policy trade-offs—that minimize the OPP deviation from zero in each year-quarter. Panel (b) plots the median OPP statistic under the inflation-target benchmark as well as its 68% and 90% percentile bands. For comparison, the median OPP series under the equal-weight benchmark and the global-optimal benchmark are also shown. The vertical red dotted line marks the official adoption of inflation-target in Brazil.

Figure 6: Mexico—Revealed policy priorities and OPP-based policy evaluation

(a) Time-varying policy weights that rationalize observed policy rate



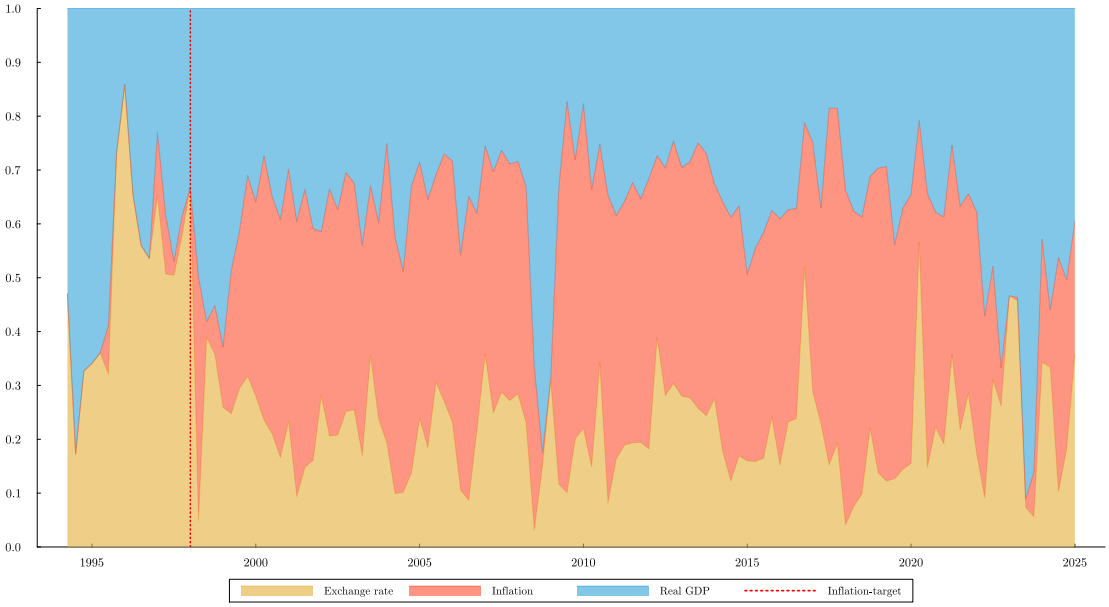
(b) OPP statistics across different constant-weight benchmarks



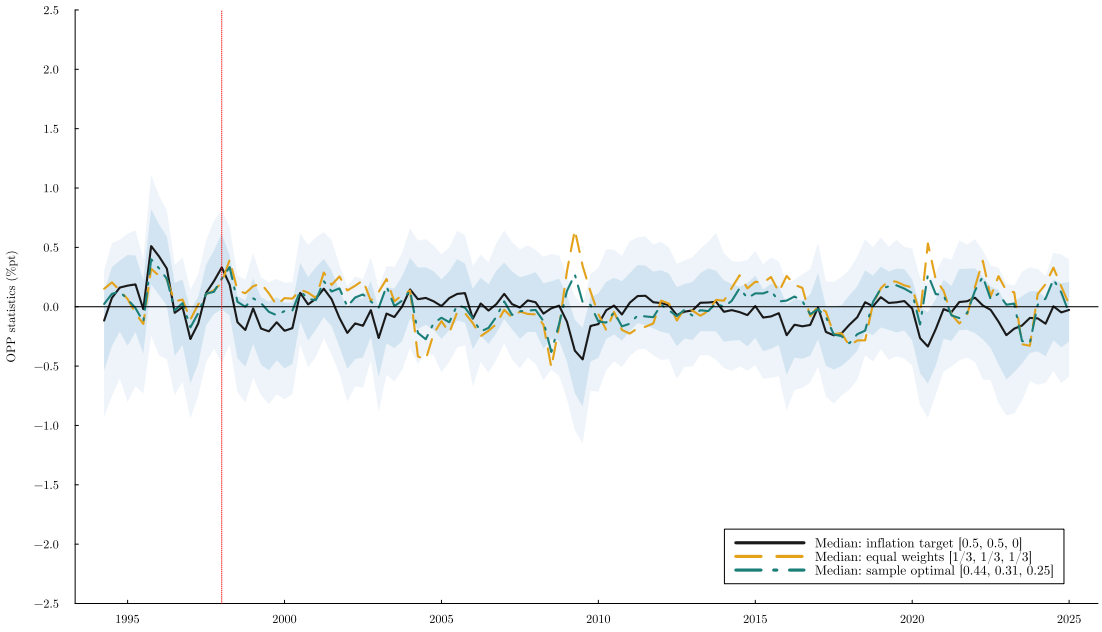
Notes: This figure evaluates the credibility of inflation-target monetary policy in Mexico. Panel (a) reports the period-specific optimal policy weights—interpreted as revealed preferences over policy trade-offs—that minimize the OPP deviation from zero in each year-quarter. Panel (b) plots the median OPP statistic under the inflation-target benchmark as well as its 68% and 90% percentile bands. For comparison, the median OPP series under the equal-weight benchmark and the global-optimal benchmark are also shown. The vertical red dotted line marks the official adoption of inflation-target in Mexico.

Figure 7: Chile—Revealed policy priorities and OPP-based policy evaluation

(a) Time-varying policy weights that rationalize observed policy rate



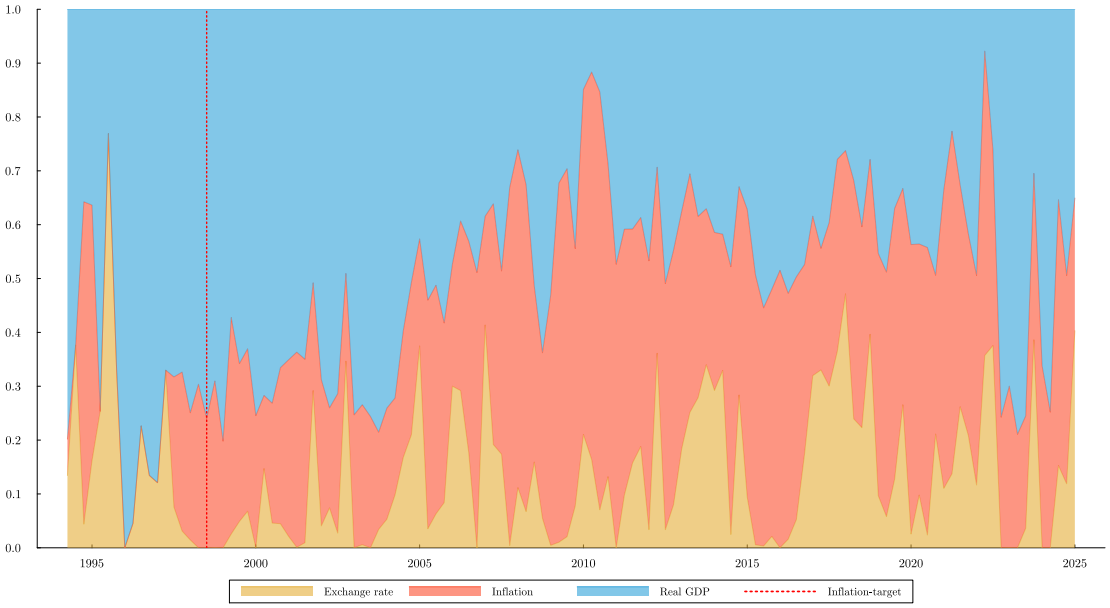
(b) OPP statistics across different constant-weight benchmarks



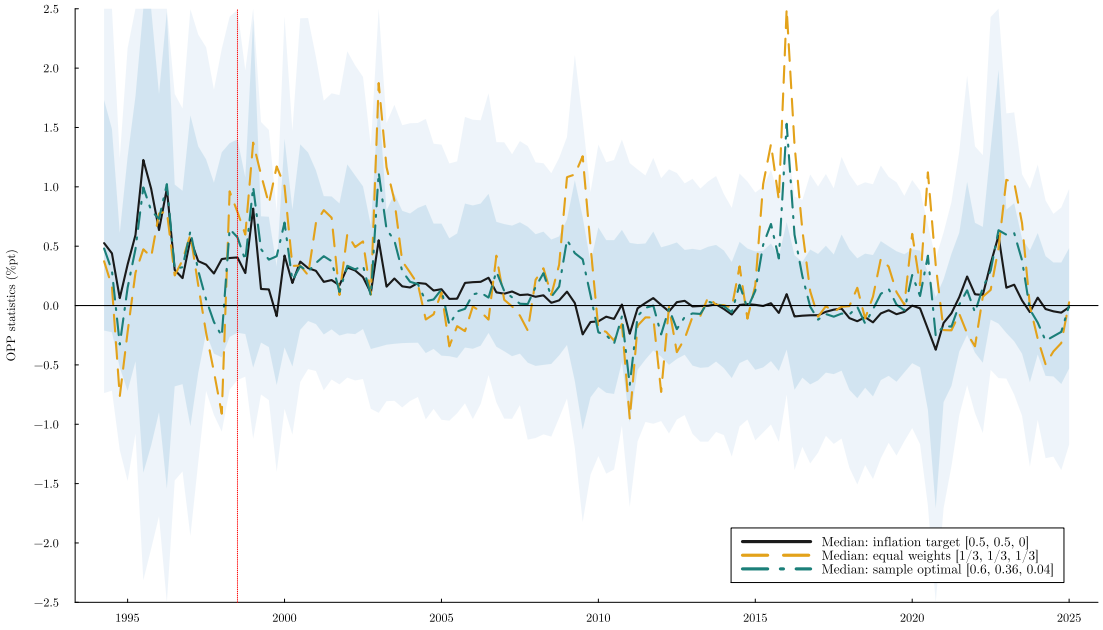
Notes: This figure evaluates the credibility of inflation-target monetary policy in Chile. Panel (a) reports the period-specific optimal policy weights—interpreted as revealed preferences over policy trade-offs—that minimize the OPP deviation from zero in each year-quarter. Panel (b) plots the median OPP statistic under the inflation-target benchmark as well as its 68% and 90% percentile bands. For comparison, the median OPP series under the equal-weight benchmark and the global-optimal benchmark are also shown. The vertical red dotted line marks the official adoption of inflation-target in Chile.

Figure 8: Colombia—Revealed policy priorities and OPP-based policy evaluation

(a) Time-varying policy weights that rationalize observed policy rate



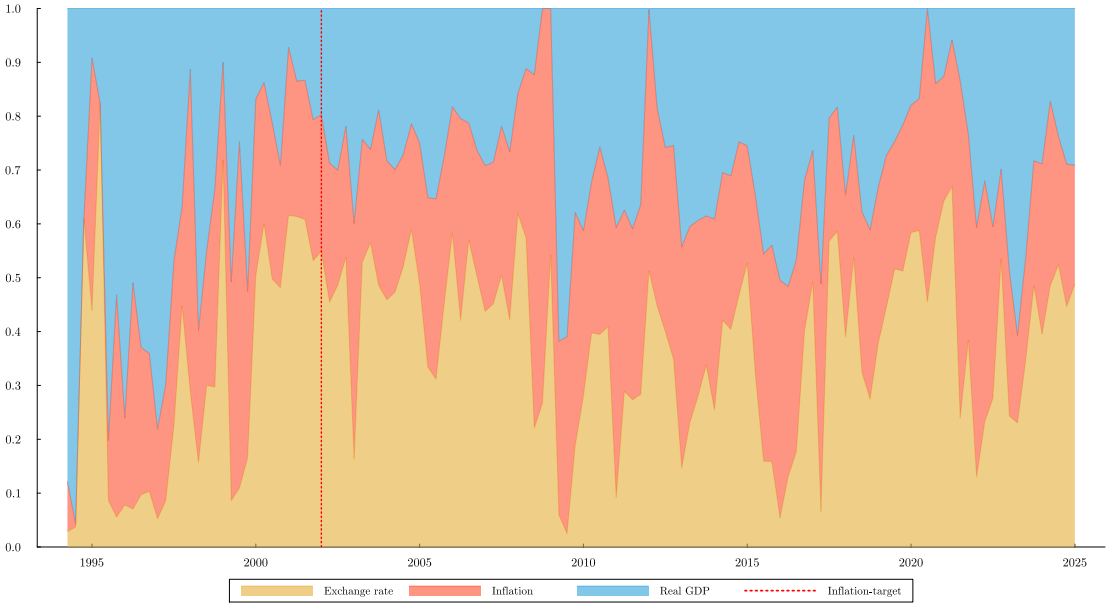
(b) OPP statistics across different constant-weight benchmarks



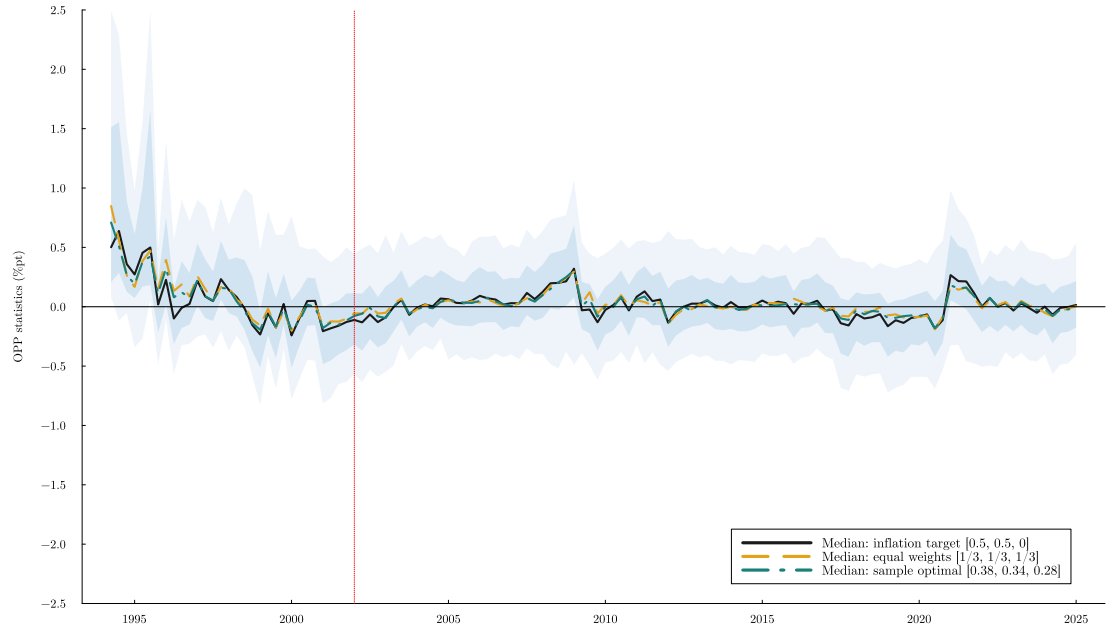
Notes: This figure evaluates the credibility of inflation-target monetary policy in Colombia. Panel (a) reports the period-specific optimal policy weights—interpreted as revealed preferences over policy trade-offs—that minimize the OPP deviation from zero in each year-quarter. Panel (b) plots the median OPP statistic under the inflation-target benchmark as well as its 68% and 90% percentile bands. For comparison, the median OPP series under the equal-weight benchmark and the global-optimal benchmark are also shown. The vertical red dotted line marks the official adoption of inflation-target in Colombia.

Figure 9: Peru—Revealed policy priorities and OPP-based policy evaluation

(a) Time-varying policy weights that rationalize observed policy rate



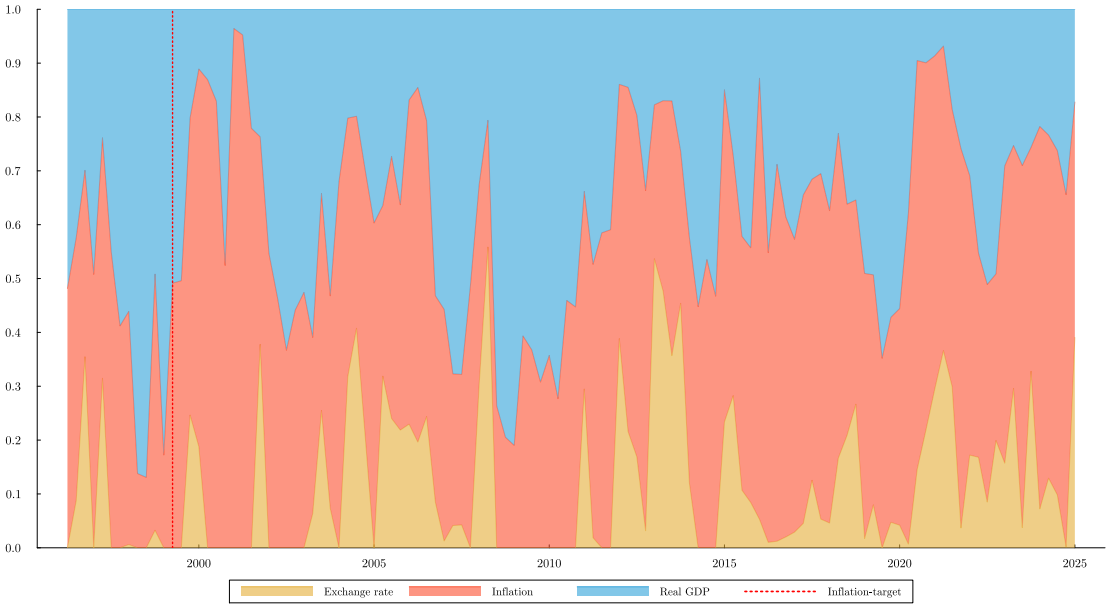
(b) OPP statistics across different constant-weight benchmarks



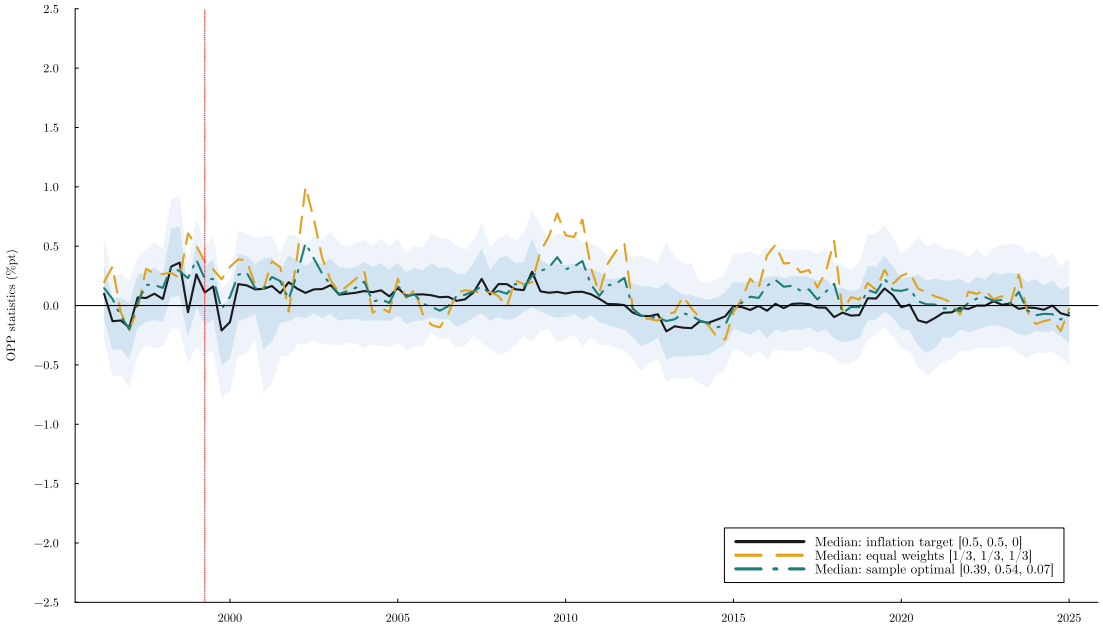
Notes: This figure evaluates the credibility of inflation-target monetary policy in Peru. Panel (a) reports the period-specific optimal policy weights—interpreted as revealed preferences over policy trade-offs—that minimize the OPP deviation from zero in each year-quarter. Panel (b) plots the median OPP statistic under the inflation-target benchmark as well as its 68% and 90% percentile bands. For comparison, the median OPP series under the equal-weight benchmark and the global-optimal benchmark are also shown. The vertical red dotted line marks the official adoption of inflation-target in Peru.

Figure 10: South Africa—Revealed policy priorities and OPP-based policy evaluation

(a) Time-varying policy weights that rationalize observed policy rate



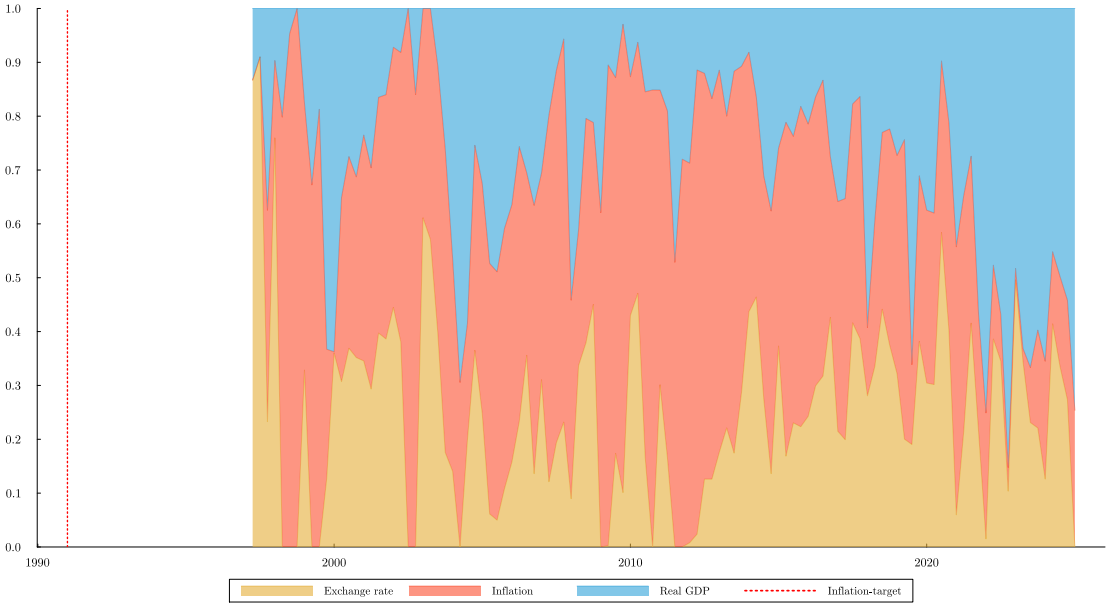
(b) OPP statistics across different constant-weight benchmarks



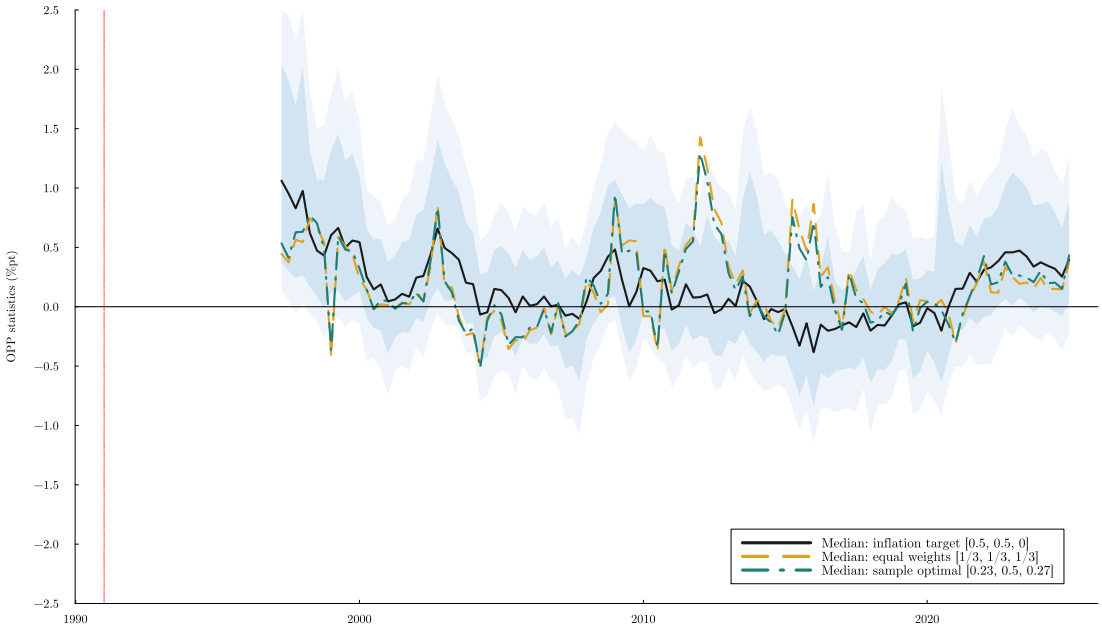
Notes: This figure evaluates the credibility of inflation-target monetary policy in South Africa. Panel (a) reports the period-specific optimal policy weights—interpreted as revealed preferences over policy trade-offs—that minimize the OPP deviation from zero in each year-quarter. Panel (b) plots the median OPP statistic under the inflation-target benchmark as well as its 68% and 90% percentile bands. For comparison, the median OPP series under the equal-weight benchmark and the global-optimal benchmark are also shown. The vertical red dotted line marks the official adoption of inflation-target in South Africa.

Figure 11: Israel—Revealed policy priorities and OPP-based policy evaluation

(a) Time-varying policy weights that rationalize observed policy rate



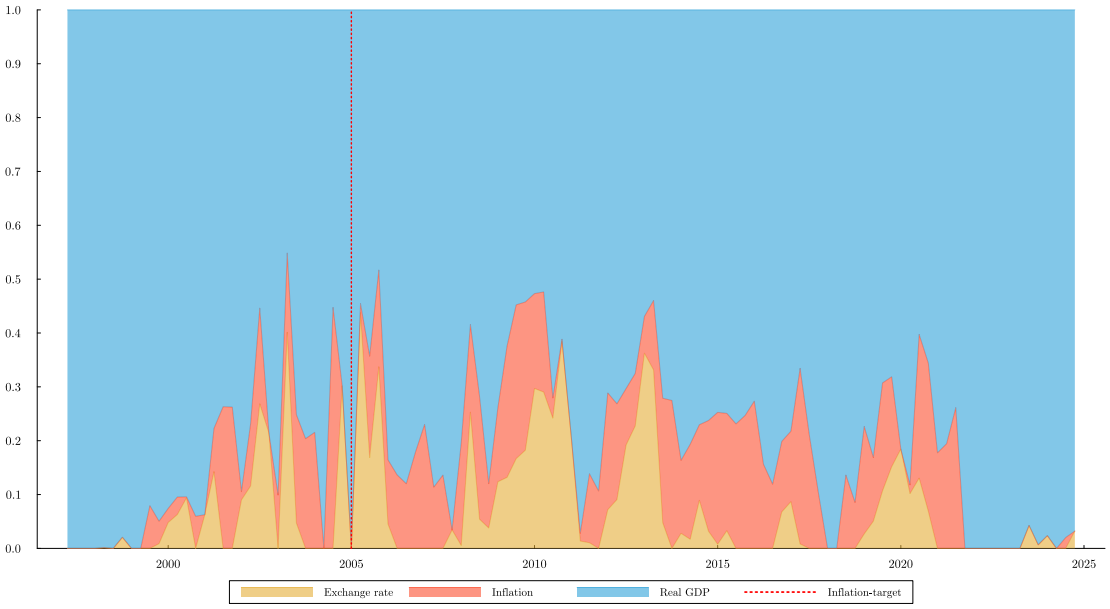
(b) OPP statistics across different constant-weight benchmarks



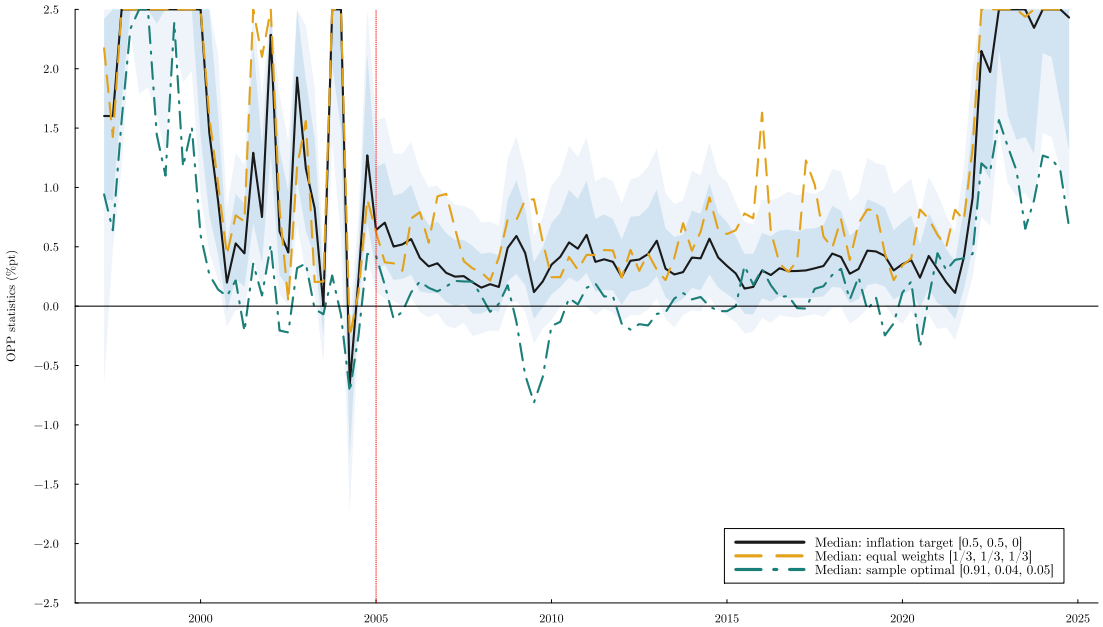
Notes: This figure evaluates the credibility of inflation-target monetary policy in Israel. Panel (a) reports the period-specific optimal policy weights—interpreted as revealed preferences over policy trade-offs—that minimize the OPP deviation from zero in each year-quarter. Panel (b) plots the median OPP statistic under the inflation-target benchmark as well as its 68% and 90% percentile bands. For comparison, the median OPP series under the equal-weight benchmark and the global-optimal benchmark are also shown. The vertical red dotted line marks the official adoption of inflation-target in Israel.

Figure 12: Turkey—Revealed policy priorities and OPP-based policy evaluation

(a) Time-varying policy weights that rationalize observed policy rate



(b) OPP statistics across different constant-weight benchmarks



Notes: This figure evaluates the credibility of inflation-target monetary policy in Turkey. Panel (a) reports the period-specific optimal policy weights—interpreted as revealed preferences over policy trade-offs—that minimize the OPP deviation from zero in each year-quarter. Panel (b) plots the median OPP statistic under the inflation-target benchmark as well as its 68% and 90% percentile bands. For comparison, the median OPP series under the equal-weight benchmark and the global-optimal benchmark are also shown. The vertical red dotted line marks the official adoption of inflation-target in Turkey.

7 Online Appendix

(Preliminary; not for circulation)

7.1 Bayesian VAR derivation

This section provides a detailed derivation of the Bayesian VAR model used in this paper.

First, we have $\mathbf{Y} \sim \mathcal{MN}(\mathbf{XB}, \Sigma, I_{T-p})$ implies the PDF is given as:

$$f(\mathbf{Y} \mid \mathbf{XB}, \Sigma, I_{T-p}) = \left(\frac{1}{2\pi}\right)^{(T-p)k/2} \left(\frac{1}{|\Sigma|}\right)^{(T-p)/2} \exp\left(-\frac{1}{2}\operatorname{tr}\left[\Sigma^{-1}(\mathbf{Y}-\mathbf{XB})'(\mathbf{Y}-\mathbf{XB})\right]\right)$$

At the same time, we have $\mathbf{B} \sim \mathcal{MN}\left(\underline{\mathbf{B}}, \underline{\mathbf{V}}, \Sigma\right)$ implies the PDF is given as:

$$f\left(\mathbf{B} \mid \underline{\mathbf{B}}, \underline{\mathbf{V}}, \Sigma\right) = \left(\frac{1}{2\pi}\right)^{(T-p)k/2} \left(\frac{1}{|\Sigma|}\right)^{(T-p)/2} \left(\frac{1}{|\underline{\mathbf{V}}|}\right)^{\frac{k}{2}} \exp\left(-\frac{1}{2}\operatorname{tr}\left[\Sigma^{-1}(\mathbf{B}-\underline{\mathbf{B}})'\underline{\mathbf{V}}^{-1}(\mathbf{B}-\underline{\mathbf{B}})\right]\right)$$

Last but not least, we have $\Sigma \sim \mathcal{IW}\left(\underline{\mathbf{S}}, \underline{\alpha}\right)$ implies the PDF is given as:

$$f\left(\Sigma\right) = \left(\frac{|\underline{\mathbf{S}}|^{\underline{\alpha}}}{\Gamma(\underline{\alpha})}\right) \left(|\Sigma|\right)^{-\left(\underline{\alpha}+\frac{T+1}{2}\right)} \exp\left(-\operatorname{tr}\left[\Sigma^{-1}\underline{\mathbf{S}}\right]\right)$$

Therefore, by the Baye's theorem, we have

$$
\begin{aligned}
f\left(\mathbf{B}, \Sigma \mid Y\right) &= \frac{f\left(\mathbf{B}, \Sigma, Y\right)}{f\left(\mathbf{Y}\right)} \\
&\propto f\left(\mathbf{Y} \mid \mathbf{B}, \Sigma\right) f\left(\mathbf{B} \mid \Sigma\right) f\left(\Sigma\right) \\
&\propto \left(\frac{1}{2\pi}\right)^{(T-p)k/2} \left(\frac{1}{|\Sigma|}\right)^{(T-p)/2} \exp\left(-\frac{1}{2}\operatorname{tr}\left[\Sigma^{-1}(\mathbf{Y}-\mathbf{XB})'(\mathbf{Y}-\mathbf{XB})\right]\right) \\
&\quad \times \left(\frac{1}{2\pi}\right)^{(T-p)k/2} \left(\frac{1}{|\Sigma|}\right)^{(T-p)/2} \left(\frac{1}{|\underline{\mathbf{V}}|}\right)^{\frac{k}{2}} \exp\left(-\frac{1}{2}\operatorname{tr}\left[\Sigma^{-1}(\mathbf{B}-\underline{\mathbf{B}})'\underline{\mathbf{V}}^{-1}(\mathbf{B}-\underline{\mathbf{B}})\right]\right) \\
&\quad \times \left(\frac{|\underline{\mathbf{S}}|^{\underline{\alpha}}}{\Gamma(\underline{\alpha})}\right) \left(|\Sigma|\right)^{-\left(\underline{\alpha}+\frac{(T-p)+1}{2}\right)} \exp\left(-\operatorname{tr}\left[\Sigma^{-1}\underline{\mathbf{S}}\right]\right) \\
&\propto \left(|\Sigma|^{-\left(\underline{\alpha}+\frac{(T-p)+1}{2}+\frac{(T-p)}{2}+\frac{(T-p)}{2}\right)}\right) \exp\left(-\frac{1}{2}\operatorname{tr}\left(\Sigma^{-1}\left((\mathbf{Y}-\mathbf{XB})'(\mathbf{Y}-\mathbf{XB})+(\mathbf{B}-\underline{\mathbf{B}})'\underline{\mathbf{V}}^{-1}(\mathbf{B}\right.\right.\right.
\end{aligned}
$$

Notice that

$$
\begin{aligned}
&(\mathbf{Y}-\mathbf{XB})'(\mathbf{Y}-\mathbf{XB})+(\mathbf{B}-\underline{\mathbf{B}})'\underline{\mathbf{V}}^{-1}(\mathbf{B}-\underline{\mathbf{B}}) \\
&= \mathbf{Y}'\mathbf{Y}-2\mathbf{B}'\mathbf{X}'\mathbf{Y}+\mathbf{B}'\mathbf{X}'\mathbf{XB}+\mathbf{B}'\underline{\mathbf{V}}^{-1}\mathbf{B}-2\underline{\mathbf{B}}'\underline{\mathbf{V}}^{-1}\mathbf{B}+\underline{\mathbf{B}}'\underline{\mathbf{V}}^{-1}\underline{\mathbf{B}} \\
&= -2\mathbf{B}'\left(\mathbf{X}'\mathbf{Y}+\underline{\mathbf{V}}^{-1}\underline{\mathbf{B}}\right)+\mathbf{B}'\left(\mathbf{X}'\mathbf{X}+\underline{\mathbf{V}}^{-1}\right)\mathbf{B}+\mathbf{Y}'\mathbf{Y}+\underline{\mathbf{B}}'\underline{\mathbf{V}}^{-1}\underline{\mathbf{B}}
\end{aligned}
$$

Using guess and verify, assume $\overline{\mathbf{V}} = (\mathbf{X}'\mathbf{X}+\underline{\mathbf{V}}^{-1})^{-1}$ and $\overline{\mathbf{B}} = \overline{\mathbf{V}}(\mathbf{X}'\mathbf{Y}+\underline{\mathbf{V}}^{-1}\underline{\mathbf{B}})$, we can show that

$$
\begin{aligned}
(\mathbf{B}-\overline{\mathbf{B}})'\overline{\mathbf{V}}^{-1}(\mathbf{B}-\overline{\mathbf{B}}) &= \mathbf{B}'\overline{\mathbf{V}}^{-1}\mathbf{B}-2\mathbf{B}'\overline{\mathbf{V}}^{-1}\overline{\mathbf{B}}+\overline{\mathbf{B}}'\overline{\mathbf{V}}^{-1}\overline{\mathbf{B}} \\
&= -2\mathbf{B}'\overline{\mathbf{V}}^{-1}\overline{\mathbf{V}}(\mathbf{X}'\mathbf{Y}+\underline{\mathbf{V}}^{-1}\underline{\mathbf{B}})+\mathbf{B}'(\mathbf{X}'\mathbf{X}+\underline{\mathbf{V}}^{-1})\mathbf{B}+\overline{\mathbf{B}}'\overline{\mathbf{V}}^{-1}\overline{\mathbf{B}} \\
&= -2\mathbf{B}'(\mathbf{X}'\mathbf{Y}+\underline{\mathbf{V}}^{-1}\overline{\mathbf{B}})+\mathbf{B}'(\mathbf{X}'\mathbf{X}+\underline{\mathbf{V}}^{-1})\mathbf{B}+\overline{\mathbf{B}}'\overline{\mathbf{V}}^{-1}\overline{\mathbf{B}}
\end{aligned}
$$

THerefore, we can rewrite

$$
\begin{aligned}
&(\mathbf{Y}-\mathbf{XB})'(\mathbf{Y}-\mathbf{XB})+(\mathbf{B}-\underline{\mathbf{B}})'\underline{\mathbf{V}}^{-1}(\mathbf{B}-\underline{\mathbf{B}}) \\
&=(\mathbf{B}-\overline{\mathbf{B}})'\overline{\mathbf{V}}^{-1}(\mathbf{B}-\overline{\mathbf{B}})-\left(-\overline{\mathbf{B}}'\overline{\mathbf{V}}^{-1}\overline{\mathbf{B}}+\mathbf{Y}'\mathbf{Y}+\underline{\mathbf{B}}'\underline{\mathbf{V}}^{-1}\underline{\mathbf{B}}\right)
\end{aligned}
$$

For the last step, notice that

$$
\begin{aligned}
f\left(\mathbf{B},\Sigma \mid Y\right) \propto &\left(|\Sigma|\right)^{-\frac{(T-p)}{2}}\exp\left(-\frac{1}{2}\operatorname{tr}\left[\Sigma^{-1}(\mathbf{B}-\overline{\mathbf{B}})'\overline{\mathbf{V}}^{-1}(\mathbf{B}-\overline{\mathbf{B}})\right)\right) \\
&\times\left(|\Sigma|\right)^{-\left(\overline{\alpha}+\frac{T+1}{2}\right)}\exp\left(-\operatorname{tr}\left[\Sigma^{-1}\left(\underline{\mathbf{S}}+\frac{1}{2}\left(\mathbf{Y}'\mathbf{Y}+\underline{\mathbf{B}}'\underline{\mathbf{V}}^{-1}\underline{\mathbf{B}}-\overline{\mathbf{B}}'\overline{\mathbf{V}}^{-1}\overline{\mathbf{B}}\right)\right)\right]\right) \\
&\frac{\left(|\Sigma|^{-\left(\underline{\alpha}+\frac{(T-p)+1}{2}+\frac{(T-p)}{2}+\frac{(T-p)}{2}\right)}\right)}{\left(|\Sigma|\right)^{-\left(\overline{\alpha}+\frac{(T-p)+1}{2}+\frac{(T-p)}{2}\right)}}
\end{aligned}
$$

Therefore, for the posterior parameters that follow the Normal-Inverse-Wishart distribution, I further assume:

$$
\overline{\mathbf{S}}\equiv\underline{\mathbf{S}}+\frac{1}{2}\left(\mathbf{Y}'\mathbf{Y}+\underline{\mathbf{B}}'\underline{\mathbf{V}}^{-1}\underline{\mathbf{B}}-\overline{\mathbf{B}}'\overline{\mathbf{V}}^{-1}\overline{\mathbf{B}}\right)
$$

As well as for $\frac{\left(|\Sigma|^{-\left(\underline{\alpha}+\frac{(T-p)+1}{2}+\frac{(T-p)}{2}+\frac{(T-p)}{2}\right)}\right)}{\left(|\Sigma|\right)^{-\left(\overline{\alpha}+\frac{(T-p)+1}{2}+\frac{(T-p)}{2}\right)}}$ to be equal to 1, this implies

$$
\overline{\alpha}=\underline{\alpha}+\frac{T-p}{2}
$$

Therefore, the posterior parameters $\left(\overline{\mathbf{B}}, \overline{\mathbf{V}}, \overline{\mathbf{S}}, \overline{\alpha}\right)$ given as follows:

$$\begin{aligned}
\overline{\mathbf{V}} &= (\mathbf{X}'\mathbf{X} + \underline{\mathbf{V}}^{-1})^{-1} \\
\overline{\mathbf{B}} &= \overline{\mathbf{V}}(\mathbf{X}'\mathbf{Y} + \underline{\mathbf{V}}^{-1}\underline{\mathbf{B}}) \\
\overline{\mathbf{S}} &= \underline{\mathbf{S}} + \tfrac{1}{2}(\mathbf{Y}'\mathbf{Y} + \underline{\mathbf{B}}'\underline{\mathbf{V}}^{-1}\underline{\mathbf{B}} - \overline{\mathbf{B}}'\overline{\mathbf{V}}^{-1}\overline{\mathbf{B}}) \\
\overline{\alpha} &= \underline{\alpha} + T
\end{aligned}$$

7.2 Optimal Policy Perturbations Derivation

This section provides a detailed derivation of the optimal policy perturbations used in this paper. Again, we start with the baseline impulse response function of endogenous variables $(x_t, \pi_t, \Delta\varepsilon_t, i_t)$ as function of parameters and structural shocks $(\xi_t, \eta_t, \epsilon_t^0)$. Since we are in the monetary discretion framework, we have $\mathbb{E}_t[\pi_{t+1}] = 0$ and $\mathbb{E}_t[x_{t+1}] = 0$. Therefore, we can rewrite the baseline model as follows:

$$\begin{aligned}
(IS) \qquad & x_t = -\frac{1}{\sigma} i_t \\
(PC) \qquad & \pi_t = \kappa x_t + \gamma \Delta\varepsilon_t + \xi_t \\
(UIP) \qquad & \Delta\varepsilon_t = i_t + \eta_t \\
(MP^0) \qquad & i_t = \phi \pi_t + \epsilon_t
\end{aligned}$$

We first start from plugging in the IS curve and UIP curve into the Phillips curve, and

then plug in the monetary policy rule into the resulting equation. This gives us:

$$\begin{aligned}\pi_t &= -\frac{\kappa}{\sigma} i_t + \gamma\left(i_t + \eta_t\right) + \xi_t \\ &= \left(\gamma - \frac{\kappa}{\sigma}\right)\phi\pi_t + \left(\gamma - \frac{\kappa}{\sigma}\right)\epsilon_t + \gamma\eta_t + \xi_t + \epsilon_t \\ &= \frac{1}{1-\phi\left(\gamma - \frac{\kappa}{\sigma}\right)}\xi_t + \frac{\gamma}{1-\phi\left(\gamma - \frac{\kappa}{\sigma}\right)}\eta_t + \frac{\gamma - \frac{\kappa}{\sigma}}{1-\phi\left(\gamma - \frac{\kappa}{\sigma}\right)}\epsilon_t\end{aligned}$$

Similarly, we can derive the expressions for x_t, $\Delta\varepsilon_t$, and i_t using the same substitution method, as well as adding the optimal policy perturbation term ϵ_t^* to the monetary policy rule.

For the optimal policy perturbation statistics δ_t^*, to solve

$$\min_{\delta_t} L_t = \min_{\delta_t} \tfrac{1}{2}\mathbf{Y}_t'\mathbf{W}\mathbf{Y}_t \quad \text{s.t.} \quad \mathbf{Y}_t = \mathcal{Y}_t^0 + \mathcal{R}^0\delta_t$$

We can rewrite the loss function as follows:

$$\min_{\delta_t} L_t = \min_{\delta_t} \tfrac{1}{2}\left(\mathcal{Y}_t^0 + \mathcal{R}^0\delta_t\right)'\mathbf{W}\left(\mathcal{Y}_t^0 + \mathcal{R}^0\delta_t\right) = \min_{\delta_t} \tfrac{1}{2}\left(\mathbf{Y}_t^{0\prime}\mathbf{W}\mathcal{Y}_t^0 + 2\delta_t\mathcal{R}^{0\prime}\mathbf{W}\mathcal{Y}_t^0 + \delta_t^2\mathcal{R}^{0\prime}\mathbf{W}\mathcal{R}^0\right)$$

Take the first order condition with respect to δ_t and set it to zero, we have:

$$\tfrac{1}{2}\left(\mathcal{R}^0\mathbf{W}\mathcal{Y}_t^0\right) + \delta_t^*\left(\mathcal{R}^{0\prime}\mathbf{W}\mathcal{R}^0\right) = 0 \implies \delta_t^* = -\left(\mathcal{R}^{0\prime}\mathbf{W}\mathcal{R}^0\right)^{-1}\left(\mathcal{R}^{0\prime}\mathbf{W}\mathcal{Y}_t^0\right)$$

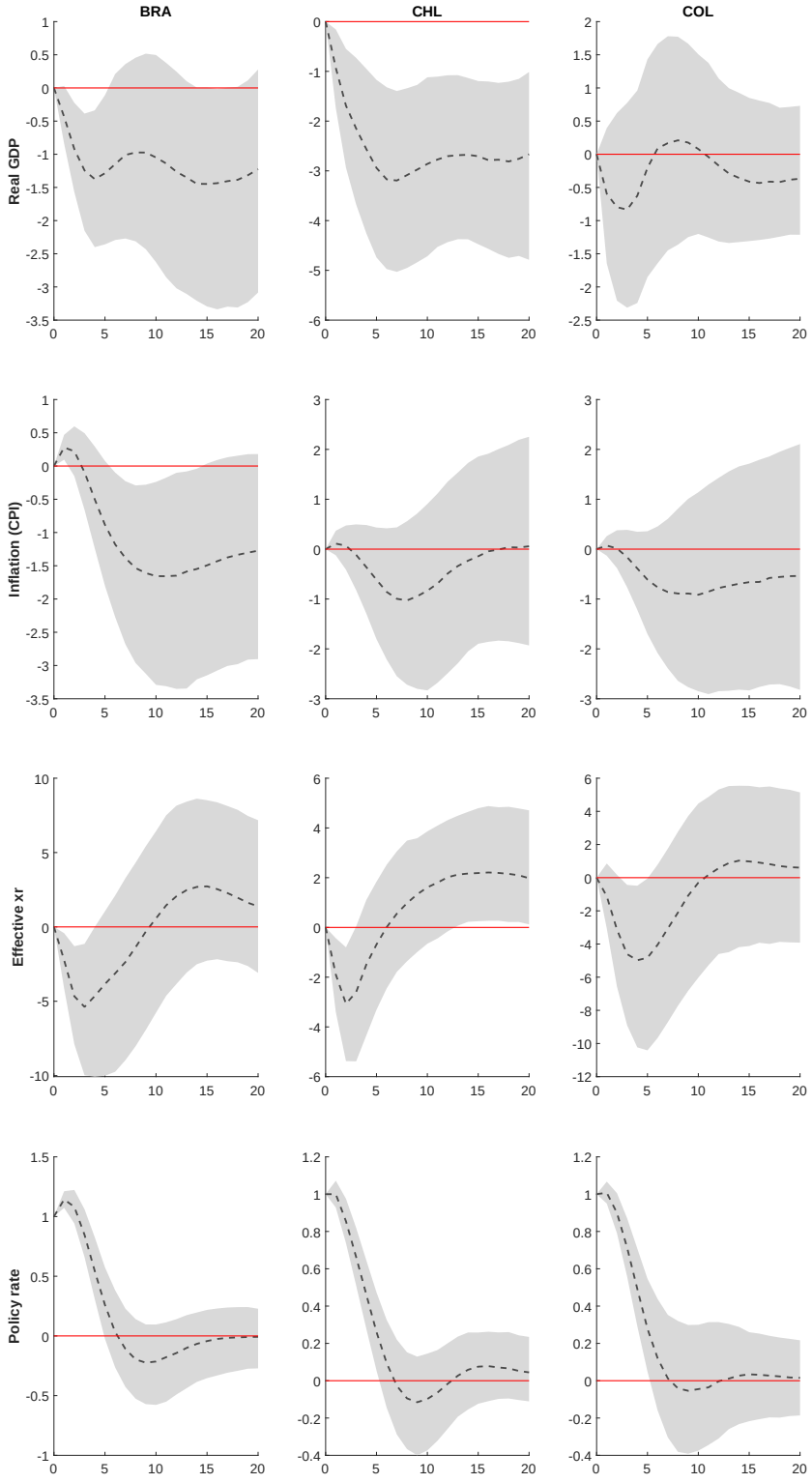
7.3 Construction of forecast path of macroeconomic variables

Therefore, for quarterly interpolation and horizon mapping, denote m as the month of the publication, where for latter years, and $q(m)$ be the function of the mapping from month to quarter, in particular, $q(1) = 1$, $q(4) = 2, q(7) = 3, q(10) = 4$. And then, since forecast horizons are pointed to the end of the year, while publication values are referring to the forecast horizon in different publication episodes, so I first place discrete

forecast points on quarterly grid. Denote $j_f \in \{0, 1, 2, 3, 4\}$ be the forward forecast, while $j_b \in \{1, 2, 3\}$ to be the back filled placeholders. For example, $(j_f, j_b) = (4, 0)$for $q(t) = 1$, and for $q(t) = 2$, $(j_f, j_b) = (3, 1)$, for $q(t) = 3, (j_f, j_b) = (2, 2)$, and last but not least, for $q(t) = 4, (j_f, j_b) = (1, 3)$. The issue is that, the EIU forecast data indeed provides forecast data up to 5 years ahead, for example, if the book is the January 2000, then it provides forecast data on the end of the year for 2000, 2001, 2002, 2003, 2004, 2005, so, this rich structure in the term structure provide me with many flexible tools to utilize this properties. In particular, for $q(t) = 1$, then $j_f \in \{4, 8, 12, 16, 20\}$ and $j_b = 1$, similar, for $q(t) = 2, j_f \in \{3, 7, 11, 15, 19\}, j_b = 1$, with the forecast horizon term structure, then I use the interpolation method to fill the quarterly horizon grids with the available forecast points and linearly interpolate the missing intermediate horizons. In other words, the focal points in each period are different based on the periodic period, that is, the forecast horizons that have real values (i.e., not intropolated) are different for each year-quarter.

8 Appendix Figures

Figure 13: Impulse responses to a 1%pt monetary policy shock (Bayesian VAR; Cholesky)



Notes:

Figure 13: (continued)

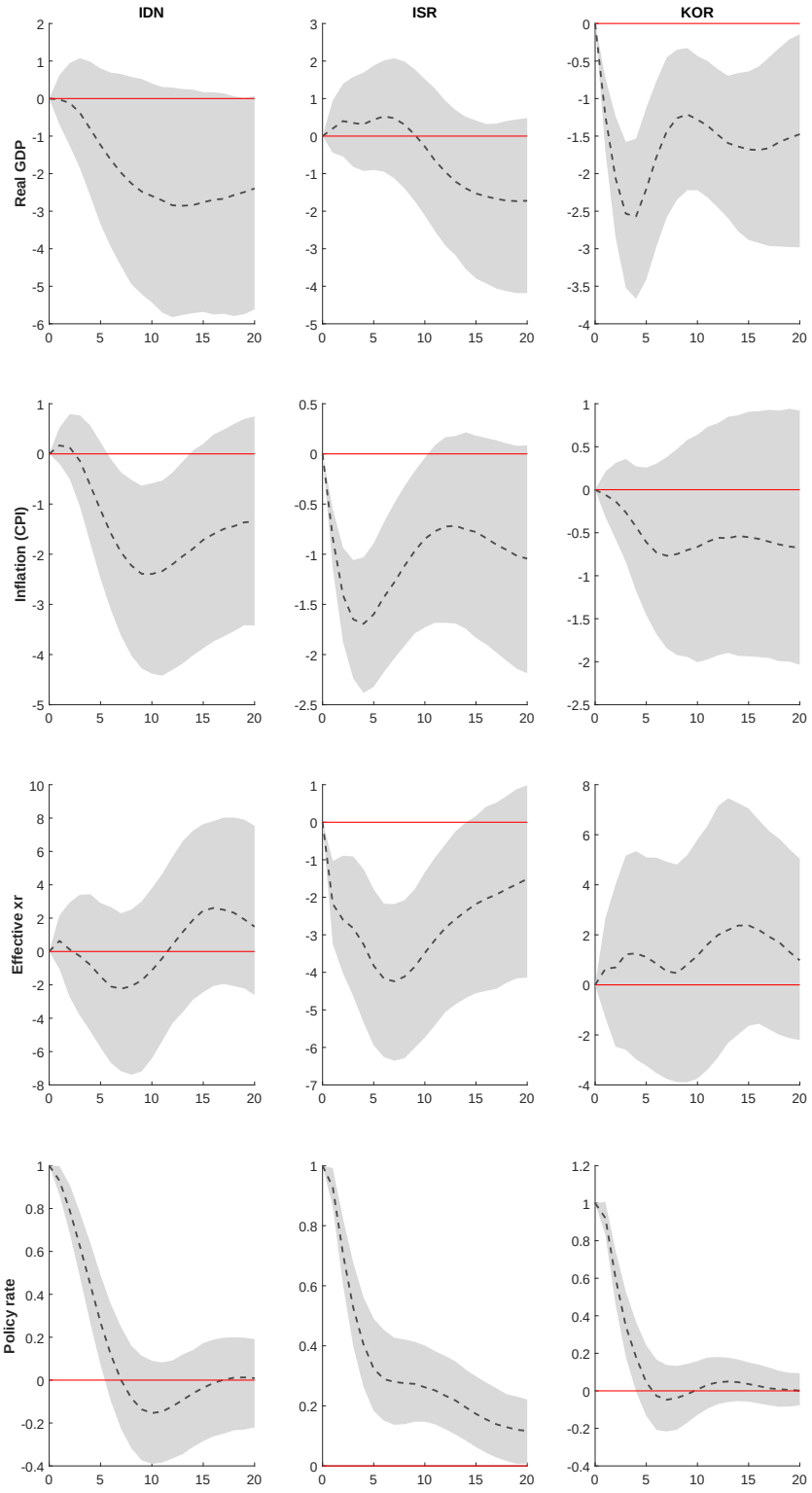


Figure 13: (continued)

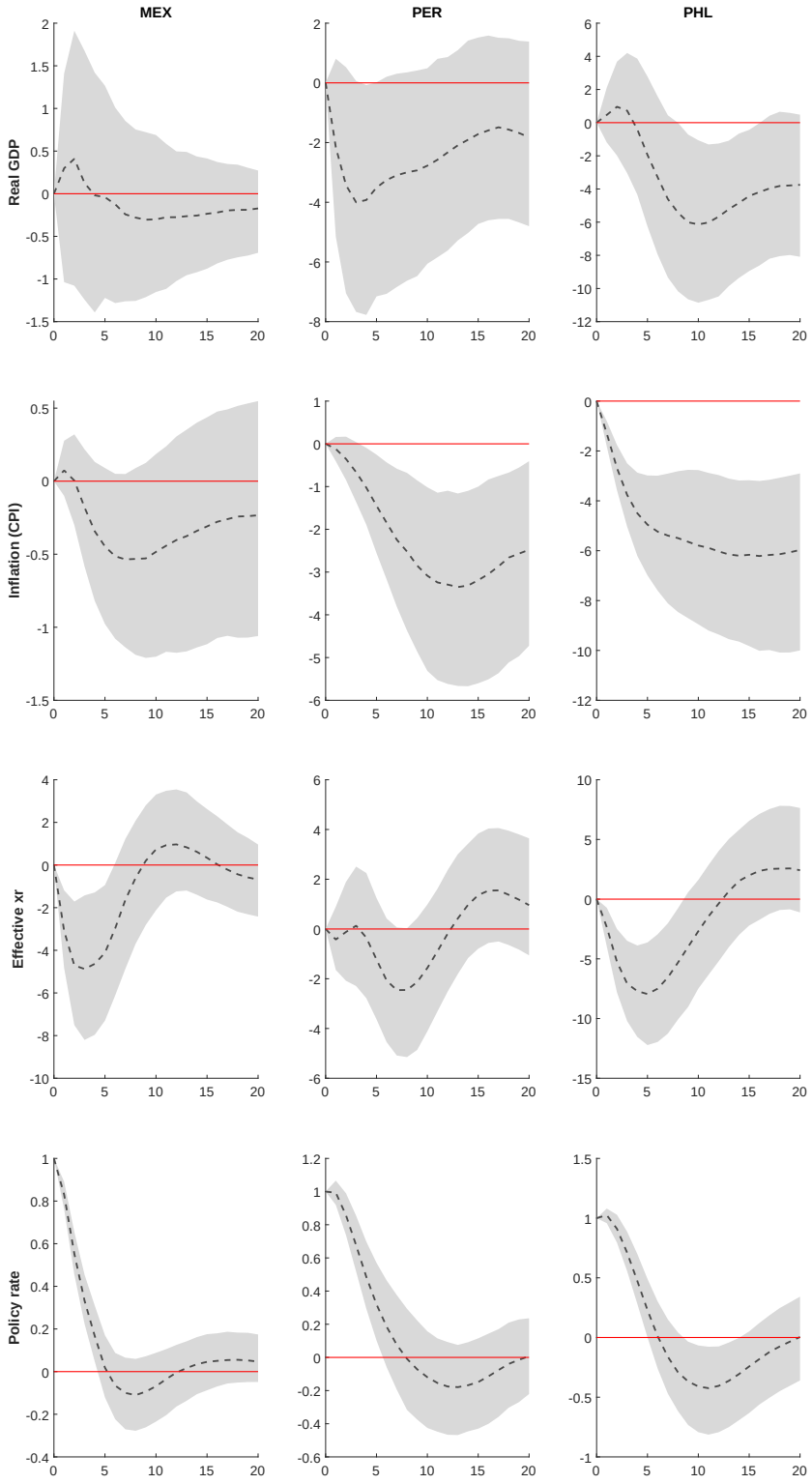
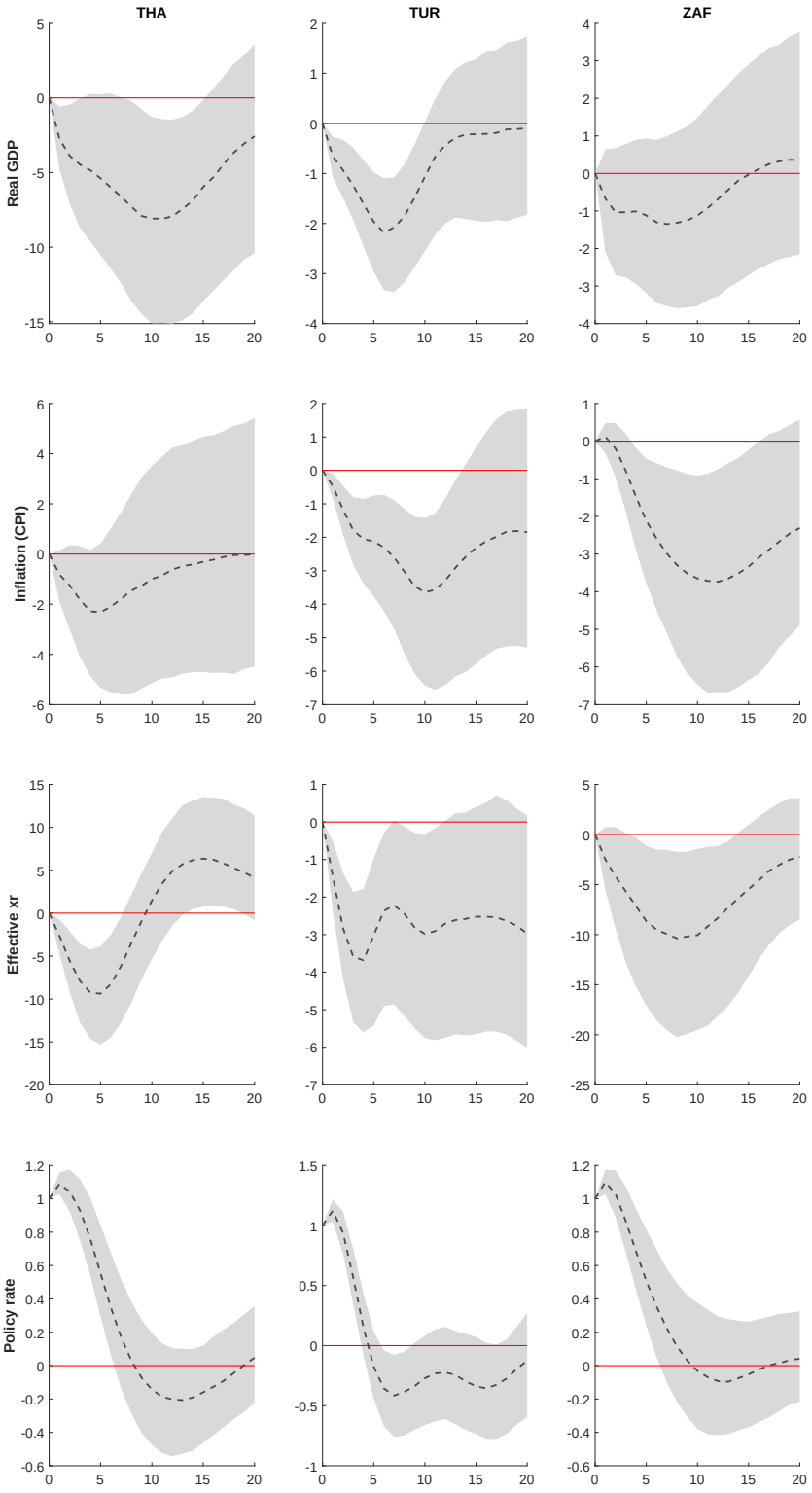


Figure 13: (continued)



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