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Transmission Channels and Macroeconomic Trade-Offs in Brazilian Monetary Policy

A TVP-SVAR-SV Analysis of the Exchange Rate and Commodity Price Effects

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Abstract

This thesis investigates how transmission channels, specifically the exchange rate channel and global commodity price channel, affect the effectiveness of monetary policy in Brazil, particularly regarding the trade-off between inflation stabilization and output loss. To account for structural changes and evolving volatilities in the Brazilian economy, the study employs a Time-Varying Parameter Structural Vector Autoregressive model with Stochastic Volatility (TVP-SVAR-SV) to estimate the dynamic effects of monetary policy shocks from 2000 to 2024. The results suggest that Brazil's monetary policy transmission has strengthened over time, reflected by declining sacrifice ratios throughout the 21^{st} century, though the exchange rate channel has frequently acted as a destabilizing factor, amplifying inflationary pressures and increasing the output cost of disinflation. In contrast, the commodity price channel displays a more ambiguous influence, at times complicating policy implementation. These findings underscore the critical role of institutional credibility, external stability, and coordinated policy responses in mitigating external shocks and enhancing the overall effectiveness of monetary policy in Brazil.

Table of Contents

List of Tables

List of Figures

1. Introduction

Central banks around the world are tasked with maintaining price stability and supporting economic activity. For example, the U.S. Federal Reserve (FED) aims to achieve the dual mandate of maximum employment and stable prices (Board of Governors of the Federal Reserve System, 2024). However, the effectiveness of monetary policy in meeting these objectives is often constrained by a range of factors. These include fiscal dominance, weak transmission mechanisms, financial market frictions, levels of informality, and external shocks - all of which can distort or delay the intended impact of policy interventions (Bean et al., 2002). These challenges tend to be more pronounced in emerging market economies, where institutional capacity, policy credibility, and heightened exposure to global financial conditions can distort policy trade-offs. An example is when an emerging market faces both high inflation and high unemployment due to commodity price shocks, limiting the central bank's ability to respond effectively. One notable example is Brazil during the period from 2014 to 2016, when economic turbulence tested the limits of monetary policy (ECB, 2016).

Hence, central banks often face a delicate balancing act: tightening monetary policy to contain inflation without triggering an excessive slowdown in economic activity (Banco Central do Brasil, n.d.-a). This tension is commonly illustrated by the short-run trade-off between output and inflation - a relationship captured by the Phillips curve (Phillips, 1958) and quantified through metrics such as the sacrifice ratio (Cecchetti & Rich, 2001, pp. 7–10). This raises a key set of questions: how exactly do monetary policy shocks transmit through an open economy like Brazil's? And to what extent do external transmission channels, such as the exchange rate and global commodity prices, affect the output cost of disinflation?

Understanding these transmission mechanisms is crucial for both policymakers and researchers. In economies vulnerable to external shocks and structural frictions, knowing how and through which channels monetary policy transmits its effects can help design more effective interventions, anticipate unintended consequences, and improve macroeconomic resilience. This is particularly important in emerging markets like Brazil, where conventional assumptions may not hold, and the cost of policy missteps can be high (Checo et al., 2024).

This thesis explores these questions by analysing Brazil's monetary transmission mechanism through a Time-Varying Parameter Structural VAR model with Stochastic Volatility (TVP-SVAR-SV). The aim of the thesis is not merely to assess whether monetary policy effectively influences inflation and output, but also to investigate the underlying mechanisms through which such effects occur. This is done by identifying the transmission channels that mediate the response to policy shocks and evaluating their contribution to Brazil's broader macroeconomic adjustment process.

In particular, this thesis focuses on two key external transmission channels: the exchange rate channel and the commodity price channel. While a broad range of mechanisms could be explored, such as credit frictions, asset price effects, or expectation dynamics, this study concentrates on these two dimensions for both empirical and structural reasons. Empirically, the exchange rate and commodity prices are observable, high-frequency variables with well-documented macroeconomic effects. Structurally, they are central to Brazil's economy due to its trade composition and financial openness. Brazil's deep integration with global markets and its role as a major exporter of primary goods make these channels especially important. The exchange rate channel captures how capital flows and currency fluctuations influence inflation and output. The commodity price channel reflects the direct and indirect effects of price shifts in goods central to Brazil's trade and fiscal revenues. Focusing on these channels allows for a more targeted and interpretable analysis of how external factors shape the domestic transmission of monetary policy in an open emerging market context (Banco Central do Brasil, n.d.-c, The Obsevatory of Economic Complexity, 2025, Combes et al., 2011, Abbas & Lan, 2020).

By estimating and comparing three model specifications, a baseline model, a model excluding the exchange rate, and a model excluding commodity prices, this thesis provides a structural decomposition of how these channels modify the effects of monetary policy over time. The analysis evaluates both the dynamic responses of inflation and output to interest rate shocks and the implied trade-offs faced by policymakers in order to determine how the effectiveness of Brazil's monetary policy is affected by the two external channels.

This effectiveness of monetary policy is assessed in two complementary dimensions. First, the direct inflation response, captured as the level effect of a monetary policy shock on the inflation rate. Second, the sacrifice ratio, defined as the cumulative output cost per percentage point reduction in inflation. A more effective policy transmission is one that achieves a larger disinflationary effect with a smaller output contraction.

Moreover, the effectiveness of monetary policy and the influence of the external transmission channels are assumed to be dependent on the prevailing economic conditions, thereby varying through time. This justifies the choice of the TVP-SVAR-SV model as it allows for examining how these dynamics evolve across different economic phases. Specifically, this is done by analysing time-varying impulse response functions for every point in time as well as estimating time-varying sacrifice ratios under each model scenario. In doing so, the thesis aims to shed light on the structural features that shape Brazil's monetary policy outcomes and offer a richer understanding of the costs and constraints central banks face when navigating inflationary environments in emerging markets.

To achieve these goals, this thesis aims to address the following problem statement:

How do the exchange rate and commodity price channels affect the effectiveness of monetary policy in Brazil, particularly in terms of the inflation-output trade-off?

To answer this question, the thesis will examine the following sub-questions:

- To what extent do monetary policy shocks affect inflation and output over time in Brazil, and how has this relationship evolved?
- What role does the exchange rate channel play in amplifying or dampening the effects of monetary policy on inflation and output?
- How do fluctuations in global commodity prices affect the effectiveness of domestic monetary policy, and how does excluding this channel influence the inflation-output trade-off?

Several methodological approaches are available to investigate this problem statement. However, to maintain a focused and coherent analytical scope, this thesis adopts specific delimitations across several dimensions. These are discussed in the following section.

1.1. Scope of the Study

This thesis is delimited along geographical, empirical, methodological, and temporal dimensions to ensure analytical clarity, consistency, and relevance. These delimitations define the scope of the thesis and frame its interpretation, particularly with respect to the assessment of monetary policy effectiveness in Brazil.

Geographically, the analysis is limited to Brazil, motivated by its role as a major emerging market with an inflation-targeting regime, a floating exchange rate system, and a strong dependence on commodity exports (Banco Central do Brasil, 2025b, The Obsevatory of Economic Complexity, 2025, Fraga, 2000). These features make Brazil a particularly suitable case for studying how external channels affect the transmission and effectiveness of monetary policy.

Monetary policy is narrowly defined as changes in the Selic rate, the short-term interest rate set by the Central Bank of Brazil (Banco Central do Brasil, BCB). Other monetary policy instruments, such as quantitative easing, forward guidance, or balance sheet operations, are excluded from the analysis. Additionally, fiscal policy interventions and structural reforms are also outside the scope. This strict focus on conventional monetary policy ensures that the estimated effects in the empirical model can be attributed to changes in the Selic rate.

Empirically, the selected variables are limited to the Selic rate, inflation rate, output gap, exchange rate, and global commodity prices. The data is sourced from the BCB, the Federal Reserve Economic Data (FRED), and the World Bank. The choice of variables reflects a balance between theoretical relevance and data availability, with a particular focus on capturing both domestic fundamentals and external factors.

Methodologically, the analysis employs a TVP-SVAR-SV model, estimated using Bayesian techniques. Accordingly, the thesis relies primarily on Bayesian estimation techniques and does not explore frequentist alternatives or competing model frameworks such as Markov-Switching VAR or local projections. The TVP-SVAR-SV model has been chosen for its capacity to account for evolving macroeconomic relationships, shifts in volatility, and structural changes in policy transmission over time. It also allows for identifying and isolating structural shocks, which is crucial for interpreting dynamic responses to monetary policy. To evaluate the trade-offs inherent in policy transmission, the model is used to compute both time-varying impulse responses and sacrifice ratios.

The full data sample is limited to monthly data for the period from 1996 to 2024. However, the first four years are used as a burn-in period to derive appropriate priors for the TVP-SVAR-SV model, which is explained in greater detail in Section 5. Consequently, the effective period for impulse response analysis runs from January 2000 to December 2024.

With the scope of the study now established, the next section outlines the overall structure of the thesis.

1.2. Structure

The thesis is structured into eleven main sections, each contributing to the overall aim of answering the central research question. The introduction outlines the motivation, problem statement, and defines the scope of the study. Section 2 presents Brazil's institutional and policy framework for monetary policy, with particular emphasis on the BCB's objectives. Section 3 develops the theoretical foundation for how monetary policy influences inflation and output, with a focus on the transmission mechanisms relevant to an open economy. Section 4 describes the selection and operationalisation of variables and provides a descriptive statistical analysis of the dataset. Section 5 details the empirical methodology, including the estimation of the TVP-SVAR-SV model and accompanying diagnostic tests for the three model specifications estimated. Section 6 analyses the impulse response functions from each model, highlighting the role of the exchange rate and commodity price channels in shaping the level effects of monetary policy shocks on output and inflation. Section 7 evaluates the time-varying sacrifice ratio across the model specifications, assessing how these channels influence the economic trade-offs associated with disinflation. Section 8 critically discusses the empirical validity of the TVP-SVAR-SV model, including the robustness of its results under alternative specifications. It also examines the identification of monetary policy shocks and compares the recursive identification strategy with alternatives such as narrative-based approaches. Section 9 considers the broader policy implications of the findings. Section 10 answers the main research question and sub-questions, while Section 11 outlines directions for future research. Finally, Appendices A through E provide supplementary material. These include a glossary of abbreviations, a complete set of impulse response functions for each model specification, and a robustness analysis that tests the sensitivity of the results to key modelling assumptions.

2. Monetary Policy Framework in Brazil

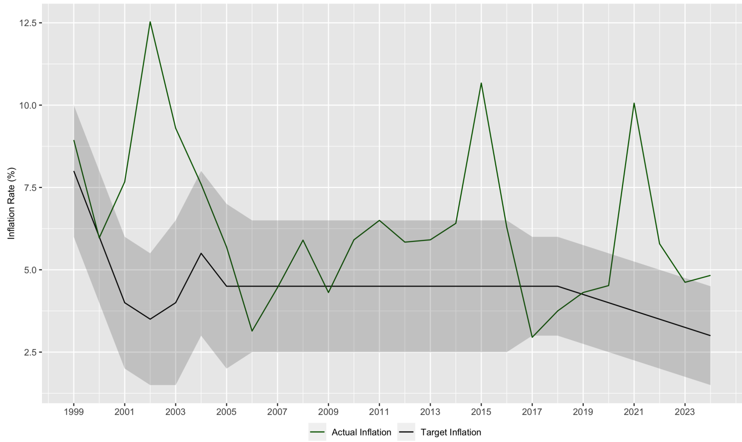
This section outlines the institutional and policy environment for monetary policy in Brazil, with a focus on the objectives of the BCB and the framework guiding their implementation. It examines the operational structure of Brazil's inflation-targeting regime and its role in anchoring inflation expectations.

Since 1999, Brazil has operated under a formal inflation-targeting regime, which defines the primary objective of monetary policy: maintaining inflation within a target range established annually by the National Monetary Council (Banco Central do Brasil, n.d.-c). The target and its range are defined in terms of the Broad National Consumer Price Index (IPCA), calculated by the Brazilian Institute of Geography and Statistics (Banco Central do Brasil, n.d.-a).

The implementation of monetary policy falls to the BCB through its Monetary Policy Committee. The main instrument used to achieve this objective is the Selic rate, the benchmark interest rate for overnight interbank loans. By adjusting the Selic rate, the BCB aims to influence aggregate demand, guide market expectations, and stabilize inflation dynamics. The system is forward-looking, emphasizing timely action to keep inflation aligned with the target. If inflation breaches the established range, the Central Bank Governor must explain the deviation and corrective measures in a public letter to the Minister of Finance. This mechanism is intended to ensure transparency and reinforce policy credibility. Brazil's inflation-targeting regime operates alongside a floating exchange rate system, allowing monetary policy to prioritize domestic price stability. Foreign exchange interventions are limited and aimed solely at curbing excessive volatility. The combination of inflation targeting, a floating exchange rate, and central bank independence constitutes the core institutional framework guiding Brazil's monetary policy (Banco Central do Brasil, n.d.-c).

Figure 2.1 illustrates Brazil's inflation-targeting performance from 1999 to 2024, showing the annual inflation target, tolerance bands, and the realized inflation rate. Although the BCB has generally succeeded in maintaining inflation within the established range, there have been five periods with notable exceptions: 2001–2003, 2015, 2017, 2021–2022, and 2024. All of these breaches, except the one in 2017, were due to the upper tolerance level being surpassed, while the inflation in 2017 was just below the lower tolerance level. Each of these breaches reflected a combination of internal and external shocks, including exchange rate volatility, global commodity price fluctuations, fiscal pressures, and supply disruptions. In each case, the BCB responded through a combination of interest rate adjustments, public communication, and, in earlier years, revisions to the target itself (Banco Central do Brasil, 2025b).

Figure 2.1: Inflation Targeting Track Record, 1999-2024



Note: The figure illustrates Brazil's inflation targeting performance from 1999 to 2024, showing the annual inflation target, the upper and lower bounds of the tolerance interval, and the actual inflation rate (measured by the IPCA). Notably, the inflation target for 2003 underwent multiple revisions. Initially set at 3.25% (with a tolerance range of 1.25%–5.25%) on 28th June 2001, it was raised to 4% and the range widened to 1.5%–6.5% on 27th June 2002. Following an inflation overshoot, the target was further increased to 8.5% on 21st January 2003, via an Open Letter from the Central Bank Governor. Similarly, the target for 2004 was first established at 3.75% (range: 1.25%–6.25%) on 27th June 2002, but was later revised to 5.5% with a wider tolerance band of 3%–8% on 25th June 2003.
Source: Own illustration of data collected from Banco Central do Brasil (2025b).

In the following section, a brief narrative of each breach episode will be provided, outlining the primary causes and the monetary policy response, as well as any lasting implications for Brazil's macroeconomic stability and policy credibility.

2.1. Episodes of Inflation Target Breaches in Brazil

Between 2001 and 2003, Brazil faced repeated breaches of its inflation target due to external shocks - including the Argentine crisis, global slowdown due to the dot-com bubble, and September 11 attacks. These led to sharp exchange rate depreciation and high inflation, compounded by rising administered prices and inflation inertia. Political uncertainty in 2002 further worsened conditions. The BCB responded with monetary tightening but avoided overcorrection to limit recession risks. By 2004, credibility began to recover through transparent communication and gradual disinflation (Banco Central do Brasil, 2002, 2003, 2004).

In 2015, inflation spiked to over 10% due to hikes in electricity and fuel prices and a major exchange rate depreciation. These were driven by global tightening and weakened fiscal credibility. Despite aggressive rate hikes, the BCB emphasized that monetary policy alone was insufficient - disinflation required restoring fiscal credibility to anchor expectations and reduce risk premia. The episode showed the limits of monetary policy when faced with cost shocks and fiscal imbalances (Banco Central do Brasil, 2016).

In 2017, Brazil saw its first inflation target undershoot as food prices plummeted due to a record harvest.

With inflation expectations anchored and the economy weak, the BCB opted not to respond to the initial price decline, which it characterised as "supply-driven and outside the reach of monetary policy". Instead, they initiated an aggressive easing cycle, reducing the Selic rate due to weak economic activity. This episode underscored the flexibility and credibility of the inflation-targeting framework (Banco Central do Brasil, 2018).

In the period 2021 to 2022 inflation breached targets in both years due to global cost shocks such as rising oil prices, supply disruptions, and the war in Ukraine alongside domestic factors like electricity tariffs and services inflation. The BCB responded with Brazil's most aggressive tightening since adopting inflation targeting (Banco Central do Brasil, 2022, 2023).

In 2024, inflation again exceeded the target due to a sharp exchange rate depreciation, drought-driven food inflation, rising demand, and worsening expectations. The BCB initially cut rates but reversed course later in the year. The delayed response likely increased the output cost of disinflation, underscoring the challenges of managing inflation in a context of fiscal instability and climate-related supply shocks (Banco Central do Brasil, 2025e).

The BCB has repeatedly relied on interest rate policy to combat inflationary pressures, with varying results depending on the economic context. To better understand how these interest rate decisions influence macroeconomic outcomes, the following section outlines the theoretical foundations of monetary policy transmission - particularly the channels through which policy affects inflation and output in an open economy like Brazil.

3. Theoretical Foundations of Monetary Policy

This section outlines the theoretical foundations of how monetary policy influences inflation and output, with a focus on the mechanisms most relevant to open economies like Brazil. It begins with a review of standard macroeconomic models describing how central banks respond to economic fluctuations and transmit those decisions through the broader economy. A separate subsection then discusses the limitations of time-invariant models and introduces the rationale for adopting a time-varying empirical framework.

In modern macroeconomics, monetary policy is typically guided by interest rate rules such as the Taylor rule. This framework assumes that central banks set the policy interest rate based on deviations of inflation from its target and output from its potential. The Taylor rule can be written as:

$$i = r^n + \pi + \phi_\pi(\pi - \pi^*) + \phi_y(Y - Y^n) \tag{3.1}$$

Here, the nominal interest rate i depends on the natural real rate r^n, current inflation π, the inflation target π^*, and the output gap $(Y - Y^n)$. The parameters ϕ_π and ϕ_y reflect the central bank's sensitivity to inflation and output deviations, respectively (Gottfries, 2013, p. 268).

The Taylor rule is based on the premise that there exists a trade-off between the inflation rate and output gap as described by the Phillips curve:

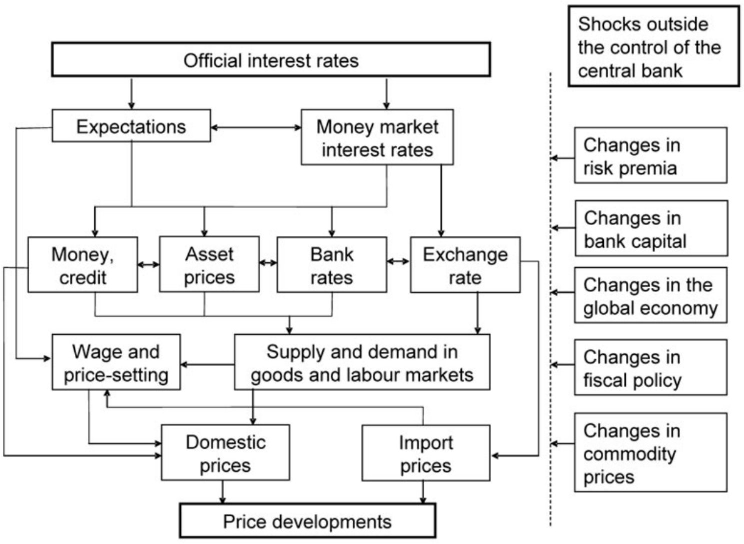
$$\pi = \pi^e + \beta\frac{Y - Y^n}{Y^n} + z \tag{3.2}$$

This relationship states that inflation π is driven by expected inflation π^e, the output gap $\frac{Y-Y^n}{Y^n}$ - measured as the deviation of actual output from its natural level - and supply shocks z. It captures how both demand-side and cost-side factors influence inflation dynamics (Gottfries, 2013, pp. 209–229 & pp. 235–250).

The link between policy rate decisions and macroeconomic outcomes such as inflation and output is not mechanical. Instead, it operates through a complex and uncertain set of transmission channels. While the Taylor rule and Phillips curve offer a high-level understanding of policy trade-offs, they do not in themselves explain how changes in the central bank's interest rate affect real activity and price dynamics. To understand these mechanisms, it is necessary to examine the transmission process by which monetary policy shocks propagate through the economy.

Central banks, including the BCB, broadly recognize the same stylized framework for monetary transmission, which has been formalized in publications by the European Central Bank (ECB) and adopted by numerous other monetary authorities (ECB, n.d., Banco Central do Brasil, 2025d, Bank of England, 2024, Sveriges Riksbank, 2025, Reserve Bank of Australia, 2025). This framework is summarized in Figure 3.1, which illustrates the sequence of effects linking interest rate changes to price developments in the economy.

Figure 3.1: The Monetary Transmission Mechanism



Note: This figure illustrates the monetary transmission mechanism, highlighting the key channels through which changes in interest rates affect the broader economy. The transmission begins with the central bank's policy rate, which influences money market interest rates and expectations. These changes then propagate through the credit, asset price, and exchange rate channels, ultimately impacting aggregate demand, supply, and inflation dynamics. The figure also acknowledges external shocks, such as global financial conditions and supply-side disturbances, which can influence the effectiveness of monetary policy.
Source: The figure have been retrieved from ECB (n.d.).

At the core of the mechanism is the central bank's policy rate, which first affects short-term money market rates and shapes expectations about future interest rates and inflation. Changes in expectations influence long-term bond yields and other forward-looking prices, altering consumption and investment decisions. For example, when the policy rate increases, borrowing becomes more expensive and expected future rates rise, which tends to reduce both household consumption and business investment.

These initial effects propagate through various channels, such as credit markets, asset prices, and exchange rates. Higher interest rates raise the cost of borrowing and discourage credit expansion, while also dampening asset prices through reduced demand for equities, real estate, and other investments. Falling asset values may constrain collateral and tighten lending conditions, further weakening economic activity. Moreover, higher rates may lead to currency appreciation, making imports cheaper and suppressing inflation as well as reducing export competitiveness and lowering net external demand.

All of these mechanisms influence aggregate demand: reduced consumption, investment, and exports contribute to a contraction in overall economic activity, which widens the output gap and dampens inflationary pressures. This demand-side cooling is also reinforced by second-round effects on wage and price-setting behaviour. As firms face weaker demand and subdued input cost pressures, they adjust pricing strategies accordingly. Inflation expectations play a crucial role here: if the central bank has sufficient credibility, an interest rate hike will lower future inflation expectations, which stabilizes wage demands and further reduces realized inflation without requiring as sharp a contraction in output.

However, the effectiveness of these channels is neither constant nor guaranteed. Transmission is subject to lags, amplification or weakening through credit markets, and interactions with external shocks - all of which are factors that are particularly relevant for open and developing economies like Brazil. As highlighted in the right-hand side of Figure 3.1, variables such as global commodity prices, international capital flows, and fiscal policy shocks can either reinforce or counteract domestic monetary impulses (ECB, n.d.).

Among these influences, two channels are particularly important in the Brazilian context and are the focus of this thesis: the exchange rate channel and the commodity price channel. As an economy with relatively high pass-through from exchange rate movements to domestic prices, and as a major exporter of primary commodities (Banco Central do Brasil, n.d.-c, The Obsevatory of Economic Complexity, 2025, Combes et al., 2011, Abbas & Lan, 2020), Brazil is especially exposed to external price shifts and currency fluctuations. These external factors can distort the expected effects of monetary tightening - such as when interest rate hikes lead to currency depreciation or rising commodity prices offset disinflationary forces. Understanding the role of these channels is therefore essential to accurately assess the real costs and effectiveness of monetary policy in Brazil.

The effectiveness of these transmission channels is not constant over time. Their impact can vary significantly across different economic conditions and policy environments. The following section will present how the thesis aims to address this issue.

3.1. Time-Varying Nature of Monetary Policy Effectiveness

While standard models assume stable relationships between policy instruments and macroeconomic outcomes, there is plenty theoretical and empirical reason to believe that the effectiveness of monetary policy varies over time. This idea has roots in both the New Keynesian and Post-Keynesian traditions, as well as in the Lucas Critique.

The Lucas Critique (Lucas, 1976) famously argued that empirical models that do not account for changes in expectations and behaviour induced by policy shifts may yield misleading results. In response, New Keynesian models introduced rational expectations and nominal rigidities, assuming agents internalize anticipated policy responses. However, these models still rest on relatively stable structural parameters and assume ergodicity - e.g., that historical patterns are informative about future dynamics (Peters, 2019).

Post-Keynesian economists go further by questioning the notion of ergodicity altogether. In their view, economies evolve under fundamental uncertainty: institutions change, preferences shift, and the probability distribution of outcomes itself is unknowable. As a result, past data may offer limited guidance for future outcomes. This perspective emphasizes the path-dependent and historically contingent nature of economic behaviour (Ferrari-Filho & Conceição, 2005, pp. 579–585).

The implication for empirical research is clear. If the macroeconomic environment, monetary regime, or transmission channels evolve over time, as they often do in emerging markets, then models assuming fixed relationships will fail to capture important dynamics. This motivates the use of time-varying approaches, such as the TVP-SVAR-SV model used in this thesis. By allowing parameters and shock variances to change over time, this framework provides a more flexible and realistic representation of how monetary policy affects inflation and output in a changing economic landscape.

The following section presents the variables used in the TVP-SVAR-SV model, including their selection, measurement, and observed dynamics. The subsequent section then outlines the formal methodology for estimating the model.

4. Data and Descriptive Statistics

This section presents the data underlying the empirical analysis. It begins with the selection and operationalisation of key variables, including details on data collection and pre-processing. This is followed by an assessment of the validity and reliability of the chosen measures, and a descriptive statistical analysis covering the period from January 1996 to December 2024.

4.1. Data Collection, Pre-Processing, and Validity

This thesis examines how the economic trade-off of monetary policy in Brazil changes through time based on the impulse response functions (IRFs) estimated from a TVP-SVAR-SV framework. Unlike traditional VAR models that assume constant parameters and generate a single set of IRFs over the entire sample, the TVP-SVAR-SV framework allows for the structural relationships between variables to change over time. This means that IRFs are estimated for each point in time, enabling the analysis to trace how the effects of a monetary policy shock on inflation and the output gap evolve across different historical periods.

Given the complexity of monetary transmission in an open economy, multiple domestic and external factors influence this dynamic relationship. To avoid overparameterisation (Enders, 2015, p. 290 & p. 336) while still capturing key transmission channels, the baseline TVP-SVAR-SV model includes five variables: the monetary policy rate, output gap, inflation, exchange rate, and global commodity prices. Inflation and output gap serve as the main indicators of macroeconomic performance, while the exchange rate and commodity prices are explicitly included to examine the role of the external sector in monetary transmission. Brazil's openness to global financial conditions and dependence on commodity exports make these channels especially relevant (The Obsevatory of Economic Complexity, 2025). By re-estimating the model under two alternative specifications, excluding first the exchange rate and then commodity prices, the analysis identifies the contribution of each channel to the propagation of monetary policy shocks and the associated policy trade-offs over time. All variables have been collected as monthly data for the period 1996M1-2024M12. Furthermore, all variables have been seasonally adjusted using the method described in United States Census Bureau (2022). An overview of the choice of variables and how these are processed is shown in Table 4.1.

These five variables provide a structured approach for analysing the economic trade-off of monetary policy through various transmission channels. However, it necessarily excludes several potentially important influences on the monetary transmission mechanism. Variables such as external interest rates, imported inflation, bank lending conditions, and asset prices are not explicitly incorporated. These exclusions are made to maintain statistical tractability and avoid overparameterisation. However, the chosen set of variables is deliberately constructed to allow a focused analysis of specific transmission channels - namely, the exchange rate and commodity price channels. By including these variables in the baseline model and then removing them in alternative model specifications, the analysis is able to isolate and quantify the role these channels play in transmitting monetary policy shocks to inflation and the output gap. Moreover, while other omitted variables may influence the transmission of monetary policy, many of their effects tend to operate through or co-move with the included variables. For example, imported inflation pressures are often reflected in domestic inflation and exchange rate dynamics. Further, global financial conditions and risk sentiment frequently impact the exchange rate. Finally, asset price fluctuations or changes in credit conditions typically feed into aggregate demand, which is proxied by the output gap. Thus, although not directly modelled, the influence of these omitted factors is at least partially embedded in the observed behaviour of the core macroeconomic variables (Banco Central do Brasil, n.d.-b). Therefore, the model retains its validity as a tool for examining the evolution of monetary policy trade-offs and isolating the contributions of key transmission channels over time.

Table 4.1: Data Overview

Variable	Measurement
Monetary Policy Rate (i)	Accumulated Selic interest rate for a given month, expressed as an annualized percentage rate based on a 252-business-day year convention; seasonally adjusted
Actual Output	GDP (in millions of BRL), deflated to 2015 prices; seasonally adjusted
Natural Output	Hodrick-Prescott trend of the measure for actual output with $\lambda = 129,600$
Output Gap ($\hat{y}$)	Percentage deviation between the measure for actual output and the measure for natural output
Inflation (π)	Year-over-year percentage change in CPI headline inflation; seasonally adjusted
Exchange Rate (ex)	Year-over-year percentage change in the nominal BRL/USD exchange rate; seasonally adjusted
Commodity Prices (ψ)	Year-over-year percentage change in the global total commodity price index (2010=100), expressed in real USDs; seasonally adjusted

Note: Overview of the data used, as well as the measurement method thereof. Data is compiled for the period 1996M1-2024M12.
Source: Data collected from Banco Central do Brasil (2025a), Banco Central do Brasil (2025c), FRED (2025a), FRED (2025c), FRED (2025d), FRED (2025e), and World Bank Group (2025).

In the following sections, the operationalisation of each of the five variables will be presented in detail, including the rationale for their selection and the methodological considerations involved. Additionally, potential alternative measures will be discussed, highlighting their advantages and limitations in comparison to the chosen measure.

4.1.1. Monetary Policy Rate

This thesis adopts the Selic rate as the operational measure of Brazil's monetary policy stance. The Selic rate, set by the BCB, functions as the benchmark short-term interest rate in the Brazilian economy. It is the primary instrument of monetary policy, directly influencing interbank lending rates and indirectly shaping broader financial conditions, such as lending rates for households and firms (BIS, n.d.).

The series used in this analysis is sourced from Banco Central do Brasil (2025c) and reflects the monthly accumulated Selic rate, expressed as an annualized percentage based on a 252-business-day year convention. This convention aligns with financial market standards in Brazil and facilitates consistent comparison over time.

The use of the Selic rate is justified by its institutional role as the primary instrument employed by the BCB to achieve its inflation target under a flexible inflation-targeting regime. Empirical studies, including Moreira et al. (2022) and dos Anjos & Moreira (2022), frequently rely on the Selic rate to capture shifts in Brazil's monetary policy stance, reinforcing its relevance for both theoretical modelling and empirical analysis. This approach is also consistent with broader macroeconomic literature, where short-term policy rates traditionally have been used as the standard indicator of monetary policy actions. In the context of the United States, for example, changes in the federal funds rate have supplanted monetary aggregates, reserve measures, and other interest rates as the primary variable for identifying monetary policy shocks, particularly within VAR frameworks (Romer & Romer, 2004, p. 1). By analogy, the Selic rate serves as the most appropriate counterpart for capturing Brazil's monetary policy stance.

Alternative measures, such as the overnight interbank rate or short-term government bond yields, may offer insight into market expectations or the transmission mechanism of monetary policy. However, these rates are ultimately anchored to expectations of the Selic rate and do not directly reflect policy decisions. Therefore, they are less suited for identifying the monetary authority's intended stance, further justifying the use of the Selic rate in this thesis.

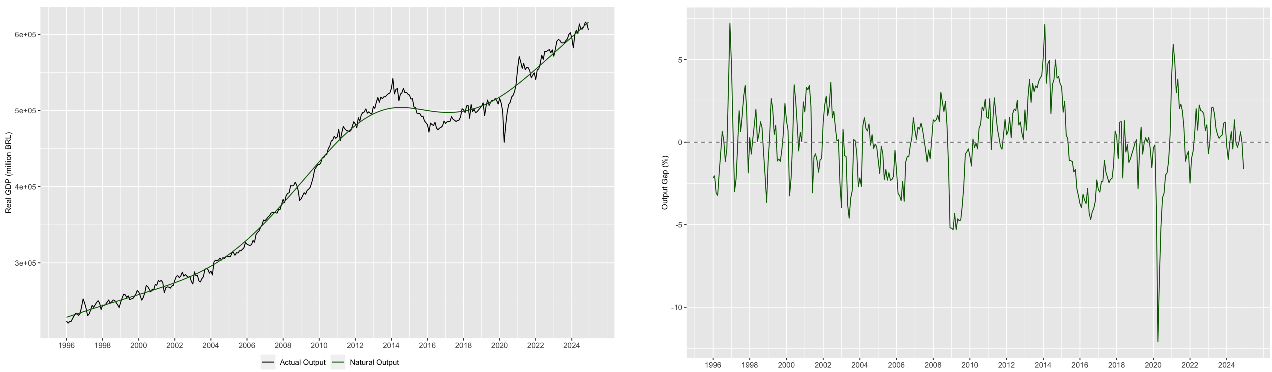
4.1.2. Output Gap

The thesis measures the output gap as the percentage deviation between the actual level of output and the natural level of output, consistent with the theoretical definition given in Equation 3.2. Actual output is proxied by real GDP, sourced from Banco Central do Brasil (2025a) as monthly values in millions of BRL at current prices. This series is converted to 2015 prices using the CPI from FRED (2025c), following the inflation adjustment procedure outlined in Federal Reserve Bank of Dallas (n.d.). The resulting real GDP series serves as the measure of actual output in the output gap calculation.

The natural level of output is an unobservable concept that requires empirical estimation (Ministry of Finance, 2020, p. 4). This thesis estimates it using the Hodrick-Prescott (HP) filter, which extracts a trend component from actual output data, following the approach of de Brouwer (1998). The chosen smoothing parameter, $\lambda = 129,600$, aligns with the recommendation of Ravn & Uhlig (2002, p. 374) for monthly data. Figure 4.1 illustrates the actual output, estimated natural output, and resulting output gap.

Figure 4.1: Estimated Measure of Natural Level of Output and Output Gap, 1996M1-2024M12

(a) Actual Output and Natural Output (b) Output Gap



Note: Figure 4.1a displays the development in the actual level of output for 1996M1-2024M12 in Brazil measured as real GDP in million BRL as well as the chosen estimate for the natural level of output estimated by a HP-trend. Figure 4.1b displays the estimated output gap in Brazil for 1996M1-2024M12 as the percentage deviation between the actual level of output and the natural level of output.
Source: Own presentation of data collected from Banco Central do Brasil (2025a), and, FRED (2025c), compiled as indicated in Table 4.1.

However, there are several limitations associated with the use of the HP filter to estimate the natural output level, which may affect the validity of the measure. One major drawback is that the HP trend can closely track actual output, potentially distorting the estimated natural level in the presence of persistent shocks. On the other hand, economic theory suggests that sustained deviations from the natural output level should not persist indefinitely. Another concern is that the HP filter is a univariate method, meaning it does not account for structural economic shifts or external influences.

A more sophisticated alternative, employed by the Danish Ministry of Finance, uses state-space models and Kalman filtering to estimate natural output. Their methodology involves assessing labour market conditions, adjusting for policy-driven employment programs, and estimating gaps in employment and labour force participation (Ministry of Finance, 2020, pp. 3-4). While these approaches provide a more detailed assessment, they require extensive modelling and parameter estimation techniques that go beyond the scope of this thesis.

For the purposes of this thesis, the HP filter is chosen due to its computational simplicity and transparency. Although alternative methods might yield slightly different estimates, de Brouwer (1998) found that output gap profiles remain broadly similar across various techniques, supporting the suitability of the HP filter.

4.1.3. Inflation Rate

The thesis measures inflation as the year-over-year percentage change in the headline Consumer Price Index (CPI), calculated as the percentage change relative to the same month in the previous year. This series is sourced from FRED (2025d).

An alternative approach would have been to use core inflation, which excludes volatile components such as food and energy prices. Core inflation is generally considered a more persistent measure of the underlying inflation trends in the economy (Kapur, 2013, p. 23). However, this thesis opts for headline inflation because it better captures the overall price level that consumers face, which is essential for assessing the full impact of monetary policy on inflation. Excluding food and energy prices would risk presenting a distorted picture of inflation dynamics, particularly in an economy where supply shocks, often driven by fluctuations in commodity prices, play a crucial role (Gordon, 2013, p. 32). Moreover, sustained deviations between headline and core inflation can emerge when food and energy prices experience permanent shocks. These persistent gaps may influence inflation expectations, leading households and firms to adjust their behaviour in ways that core inflation alone would not capture (Mishkin, 2007).

Another potential measure of inflation would have been the deviation from the central bank's inflation target. This approach aligns with the Taylor Rule framework, where monetary policy decisions respond to whether inflation is above or below target as described in Equation 3.1. However, this is not feasible in this thesis, as Brazil did not implement an official inflation-targeting regime until 1999 (BIS, n.d.). This does align with the period this thesis aims to investigate, hence it is not feasible to make the analysis with the inflation target. Furthermore, Brazil's inflation-targeting framework has evolved significantly over time. Unlike economies with a fixed inflation target, Brazil adjusts its target based on economic conditions and only sets an explicit target for the current year (Banco Central do Brasil, 2025b), which may introduce uncertainty for households and firms. This evolving nature of the target could make it less reliable as a benchmark for long-term inflation expectations, further justifying the use of headline CPI rather than a deviation-from-target measure.

4.1.4. Exchange Rate

The exchange rate is measured as the year-over-year percentage change in the BRL/USD nominal exchange rate, based on monthly data collected from 1995M1 to 2024M12. This transformation reflects persistent trends and turning points in Brazil's exchange rate dynamics in response to global financial conditions and domestic policy changes. The data is sourced from FRED (2025a).

The choice of the BRL/USD exchange rate is justified by the USD's central role in the global economy. As the dominant global reserve currency and unit of account for most international commodity and capital transactions, the USD plays a central role in shaping the external environment faced by emerging markets, including Brazil. The depth, liquidity, and perceived safety of US financial markets contribute to the dollar's persistent dominance in global trade and investment flows (Prasad, 2014).

Brazil's economic structure reinforces the relevance of the USD. The country is heavily reliant on commodity exports, such as soybeans, iron ore, and crude oil, which are almost universally priced and traded in USDs (The Obsevatory of Economic Complexity, 2025). Additionally, a large share of Brazil's external debt and foreign direct investment inflows are denominated in or influenced by the USD, making the BRL/USD exchange rate a key variable in the monetary transmission mechanism (U.S. Department of State, n.d.). Moreover, the US exchange rate serves as the most widely followed benchmark in financial markets, thereby capturing capital flow sensitivity, and reflects a significant portion of Brazil's trade and financial interactions (Goswami et al., 2023). Therefore, the inclusion of the BRL/USD exchange rate ensures the model meaningfully accounts for external shocks and their role in Brazil's monetary policy transmission.

An alternative measure of the exchange rate is a trade-weighted effective exchange rate constructed using Brazil's major trading partners. To check the sensitivity of the findings obtained in the thesis to the BRL/USD exchange rate versus a trade-weighted effective exchange rate, a robustness analysis is presented in Appendix E.

4.1.5. Commodity Prices

In the thesis, the commodity prices are operationalised as the year-over-year percentage change in the World Bank's Total Commodity Price Index in real USDs. The data is sourced from the World Bank Group (2025), and is commonly referred to as "The Pink Sheet.". The raw index reflects the weighted average prices of a broad set of internationally traded commodities, including energy products, metals, food, and raw materials, expressed in nominal USDs and normalized to 2010 = 100. The raw data is deflated using the U.S. CPI, sourced from FRED (2025e). The US CPI is first reindexed from 2015 = 100 to 2010 = 100 in order to match the base year of the commodity index. Real commodity prices are then computed using the procedure described in Fedeal Reserrve Bank of Dallas (n.d.):

$$\text{Real Commodity Index} = \frac{\text{Nominal Commodity Index}}{\text{Inflation Index}} \times 100 \tag{4.1}$$

Finally, the real index is transformed into year-over-year percentage changes.

The use of this composite index is motivated by Brazil's heavy reliance on commodity exports which constitute a large share of the country's trade balance and fiscal revenues (The Obsevatory of Economic Complexity, 2025). Movements in global commodity prices affect Brazil's output, inflation, and exchange rate through changes in export income, domestic input costs, and investor sentiment.

While a commodity price index specifically weighted by Brazil's export composition would be ideal, such a series is not publicly available with sufficient coverage or frequency over the full sample period. Therefore, the World Bank Total Commodity Price Index serves as the most viable alternative, offering comprehensive, high-frequency data that effectively captures global commodity shocks relevant for Brazil's macroeconomic dynamics.

With the measurement and rationale for each variable established, the following section turns to a descriptive statistical analysis of the dataset, providing insights into their historical trends and co-movements.

4.2. Descriptive Statistical Analysis

This section presents a descriptive statistical analysis of the selected macroeconomic variables over the period from January 1996 to December 2024. The aim is to provide an initial overview of each variable's characteristics, as well as potential relationships among them, thereby offering a preliminary sense of how these dynamics align with the theoretical expectations outlined in Section 3.

Table 4.2 reports key summary statistics, including the mean, standard deviation, minimum, and maximum values for each variable. These metrics offer insights into the magnitude, variability, and distributional properties of the data, which are crucial for the subsequent empirical analysis.

Table 4.2: Descriptive Statistics

Variable	Mean	Standard Deviation	Minimum	Maximum
Monetary Policy Rate	14.27	7.46	1.90	45.90
Output Gap	-0.03	2.40	-12.10	7.20
Inflation Rate	6.48	3.31	1.64	22.04
Exchange Rate	4.49	16.36	-36.82	41.47
Commodity Prices	-2.00	26.92	-90.09	46.52

Note: Own calculations of descriptive statistics of the variables for the monetary policy rate, output gap, inflation rate, exchange rate, and commodity prices.
Source: Own presentation of data collected from Banco Central do Brasil (2025a), Banco Central do Brasil (2025c), FRED (2025a), FRED (2025c), FRED (2025d), FRED (2025e), and World Bank Group (2025), compiled as indicated in Table 4.1 and processed in accordance with the methodology in Section 4.1.

As shown in Table 4.2, the monetary policy rate has a relatively high mean of 14.27% and a standard deviation of 7.46%, highlighting the volatility of Brazil's interest rate policy over the sample period. The rate ranges from a minimum of 1.90%, reflecting periods of aggressive monetary easing, to a peak of 45.90%, observed during the late 1990s in response to high inflation as seen in Figure 4.3a. This wide span captures the BCB's shifting stances between contractionary and expansionary policy in response to evolving macroeconomic pressures.

The output gap has a mean close to zero at -0.03%, suggesting that over time the Brazilian economy has fluctuated around its potential. However, the standard deviation of 2.40% and a range from -12.10% to 7.20% underscore the country's pronounced economic cycles. The deepest negative values correspond to significant recessions, such as those following financial crises in 2008 and the COVID-19 lockdown as seen in Figure 4.2a.

Inflation shows a mean of 6.48% with a standard deviation of 3.31%, reflecting persistent price instability throughout the period. The range is particularly striking: from a low of 1.64%, indicative of successful inflation targeting, to a high of 22.04%, a level more typical of the late 1990s or moments of macroeconomic uncertainty.

Commodity prices have a mean of -2%, indicating an overall decrease in the commodity prices over the period. The standard deviation is 26.92%, indicating a large degree of volatility. The largest decrease in commodity prices has a value of -90.09% and the largest increase consist of 46.52%.

Finally, the exchange rate presents a mean of 4.49% and a standard deviation of 16.36%, reflecting considerable volatility in the value of the BRL. The range spans from a low of -36.83% to a high of 41.47%. These swings mirror both domestic vulnerabilities and external shocks.

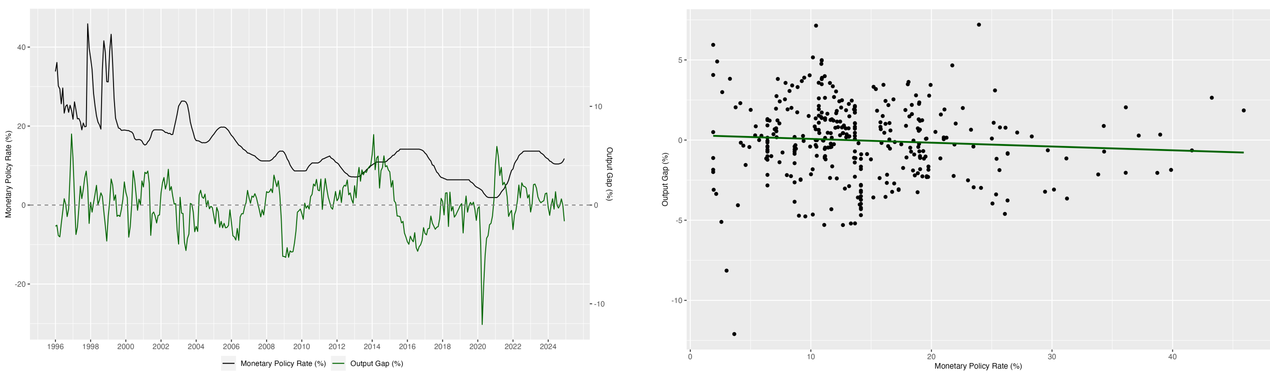
The subsequent sections provide an analysis of each variable's historical evolution and a correlation analysis to explore potential co-movements. These descriptive insights lay the groundwork for the more formal empirical modelling presented in Section 5 along with the conclusions derived hereof in Sections 6 and 7.

4.2.1. Monetary Policy Rate and Output Gap

Figure 4.2a illustrates the historical evolution of the monetary policy rate and the output gap from January 1996 to December 2024. A generally inverse relationship is evident: increases in the policy rate often coincide with declines in the output gap, consistent with standard macroeconomic theory. According to the theory, higher interest rates raise the cost of borrowing, dampening consumption and investment. They also tend to appreciate the domestic currency, making exports less competitive abroad. Together, these channels reduce aggregate demand and push output below its potential level. However, this relationship is not uniform across the entire period. During the global financial crisis, both the monetary policy rate and the output gap declined. This likely reflects an expansionary policy response aimed at mitigating the sharp contraction in economic activity. A similar deviation is observed between 2015 and 2016, when a negative output gap coincided with a modest rise in interest rates. In this case, external shocks, in the form of falling commodity prices, were the primary drivers of the downturn (Cuevas et al., 2018, pp. 16–26). Despite weak domestic demand, inflationary pressures during this period, as shown in Figure 4.3a, constrained the BCB's ability to ease monetary policy. Concerns over stagflation, a situation in which inflation rises despite weak economic activity, meant that further rate cuts could have risked exacerbating inflation, despite the recessionary conditions. From 2020 onward, the COVID-19 pandemic triggered a sharp contraction in output gap, followed by a rapid recovery. The policy rate initially remained low to support demand, but began rising sharply in 2022, reflecting a delayed policy adjustment.

Figure 4.2: Monetary Policy Rate and Output Gap

(a) Historical Development (b) Correlation Analysis



Note: Figure 4.2a illustrates the historical evolution of the monetary policy rate and the output gap from January 1996 to December 2024. Figure 4.2b further presents the correlation between these two variables over the same period, accompanied by a linear regression with a slope coefficient of -0.0237.
Source: Own presentation of data collected from Banco Central do Brasil (2025a), Banco Central do Brasil (2025c), and FRED (2025c), as described in section 4.1, compiled as indicated in Table 4.1 and processed in accordance with the methodology in Section 4.1.

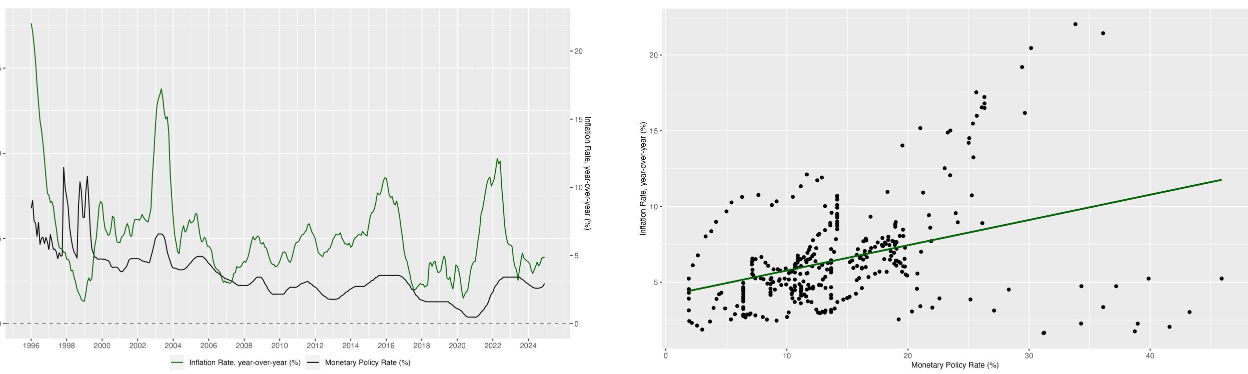
Figure 4.2b plots the relationship between the monetary policy rate and the output gap, revealing a weak but negative correlation, with a slope coefficient of -0.0237. This aligns directionally with theoretical expectations: higher interest rates are associated with a lower output gap. However, the small magnitude reflects the complexity of real-world dynamics, where monetary policy may respond endogenously to economic conditions. As Figure 4.2a shows, interest rate cuts during recessions may act to cushion output losses rather than drive expansions, meaning the observed output gap might have been even larger in the absence of such interventions, which a simple correlation analysis fails to capture. This interpretation is consistent with macroeconomic theory, where interest rates influence output through multiple demand channels. Additionally, the long-run downward trend in interest rates over the period may also affect the strength of the observed correlation.

4.2.2. Monetary Policy Rate and Inflation Rate

In Figure 4.3a the development of monetary policy rate and inflation rate is presented. Both variables display considerable volatility, yet their relationship broadly reflects the principles of inflation-targeting frameworks, where interest rates are adjusted in response to deviations of inflation from target levels. Between 1996 and 2000, inflation remained elevated, with values exceeding 20%. In response, the monetary policy rate rose steeply, peaking above 40%, in an effort to bring inflation under control. A subsequent inflationary spike between 2000 and 2002, where inflation surpassed 15%, was followed by a sharp policy adjustment. The policy rate was raised further before both variables began to decline rapidly by the end of 2003, reflecting BCB's efforts to re-anchor expectations and stabilize prices. From 2005 to 2014, inflation was more contained, generally fluctuating between 2.5% and 7%. During this period, the monetary policy rate remained relatively stable, ranging between 10% and 20%, suggesting a more predictable macroeconomic environment and a maturing inflation-targeting regime. In contrast, the period from 2014 to 2016 saw a marked increase in inflation, while the policy rate rose only modestly and gradually, reflecting the challenges of stagflation. As shown in Figure 4.2a, this period coincided with a negative output gap, limiting BCB's ability to respond aggressively without risking further contraction. This policy trade-off, central to the Taylor Rule, highlights the tension between stabilizing inflation and supporting output. More recently, from 2020 onward, inflation began to climb sharply, peaking in 2021–2022 at 12%. Initially, the policy rate remained low, as authorities sought to support the economy in the wake of the COVID-19 shock. However, as inflation persisted, the monetary policy rate was increased significantly in 2022, reflecting a delayed but forceful policy response aimed at curbing inflationary pressures and re-establishing credibility (Banco Central do Brasil, 2022, 2023).

Figure 4.3: Monetary Policy Rate and Inflation Rate

(a) Historical Development (b) Correlation Analysis



Note: Figure 4.3a illustrates the historical evolution of the monetary policy rate and the inflation rate from January 1996 to December 2024. Figure 4.3b further presents the correlation between these two variables over the same period, accompanied by a linear regression with a slope coefficient of 0.1669.
Source: Own presentation of data collected from Banco Central do Brasil (2025c) and FRED (2025d), compiled as indicated in Table 4.1 and processed in accordance with the methodology in Section 4.1.

Figure 4.3b illustrates the correlation between the inflation rate and the monetary policy rate, showing a relative strong positive relationship. This suggests that increases in the policy rate are often associated with higher inflation. The estimated slope coefficient of 0.1669 implies that for each 1 percentage point rise in the monetary policy rate, inflation increases by approximately 0.17 percentage points. This relationship, however, contrasts with the theoretical framework outlined in Section 3, which predicts that higher monetary policy rates should reduce inflation by dampening aggregate demand. One possible explanation for this apparent contradiction is that rising inflation may prompt the central bank to raise the monetary policy rate as a response, aligning with the Taylor Rule in Equation 3.1. In this case, the observed positive correlation could reflect a reactionary policy stance rather than a direct effect of interest rate hikes on inflation. This also implies that simple correlation analysis fails to capture the direct effect of interest rate hikes on inflation, justifying the need for more sophisticated methods for analysing this relationship.

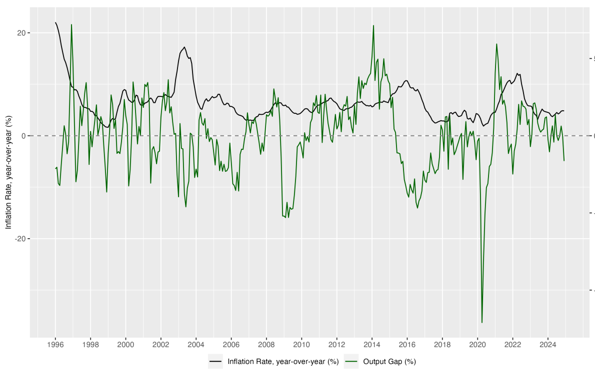
The scatter plot also reveals significant variability in the strength of this correlation. While the general trend is positive, deviations are noticeable. For example, between 2014 and 2016, despite rising inflation, the monetary policy rate remained largely stable. Additionally, the long-term downward trend in the policy rate may have influenced the observed relationship, suggesting potential structural shifts in monetary policy that warrant further exploration.

4.2.3. Output Gap and Inflation Rate

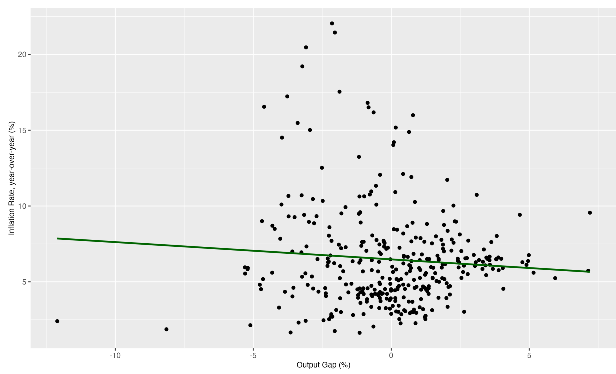
Figure 4.4a depicts the historical evolution of inflation and the output gap from 1996 to 2024. The relationship between the two variables is mixed, with some periods showing a positive association and others a negative one. Notably, the negative episodes tend to be more pronounced, featuring sharp contractions in output alongside rising inflation - indicative of stagflationary pressures. Examples include the period before the 2000s and again around 2015–2017, when inflation remained elevated despite a negative output gap. In contrast, during the global financial crisis in 2009, both inflation and the output gap declined, in line with Phillips curve predictions, where weaker demand leads to lower inflation.

Figure 4.4: Output Gap and Inflation Rate

(a) Historical Development



(b) Correlation Analysis



Note: Figure 4.4a illustrates the historical evolution of the output gap and inflation rate from January 1996 to December 2024. Figure 4.4b further presents the correlation between these two variables over the same period, accompanied by a linear regression with a slope coefficient of -0.1138.

Source: Own presentation of data collected from Banco Central do Brasil (2025a), FRED (2025c), and FRED (2025d), compiled as indicated in Table 4.1 and processed in accordance with the methodology in Section 4.1.

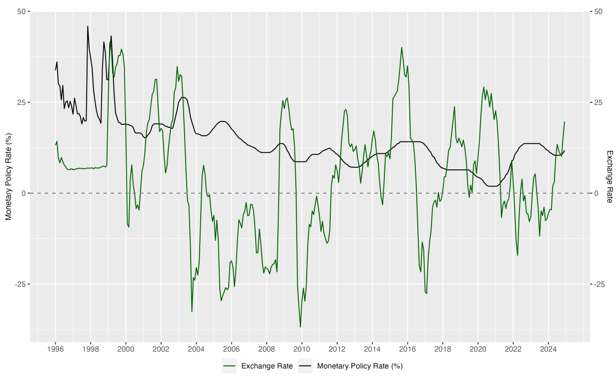
However, the correlation analysis in Figure 4.4b reveals a weak negative relationship, with a slope of -0.1138, offering limited support for the theoretical expectation. This may reflect the influence of additional policy variables, particularly monetary policy. For instance, during 2003–2004, rising inflation was accompanied by higher interest rates as observed in Figure 4.3. This likely contributed to the negative output gap by dampening demand. These counteracting forces may obscure the direct relationship between inflation and output, justifying the need for more sophisticated modelling approaches to properly examine the relationship.

4.2.4. Exchange Rate, Monetary Policy Rate, Output Gap and Inflation Rate

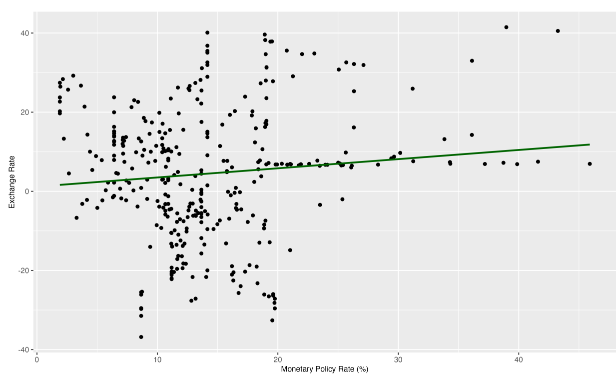
Figures 4.5a, 4.5c and 4.5e depict the historical evolution of the exchange rate, monetary policy rate, output gap, and inflation rate from 1996 to 2024. In Figure 4.5a the historical development of the monetary policy rate and the exchange rate can be observed. The exchange rate is generally declining but do have movements up and down during the declining trend. Several of the increases are accompanied by increases in the exchange rate which aligns with theoretical expectations. However, an inverse relationship can also be observed in several periods as in 2020 (COVID-19 period).

Figure 4.5: Exchange Rate, Monetary Policy Rate, Output Gap, and Inflation Rate

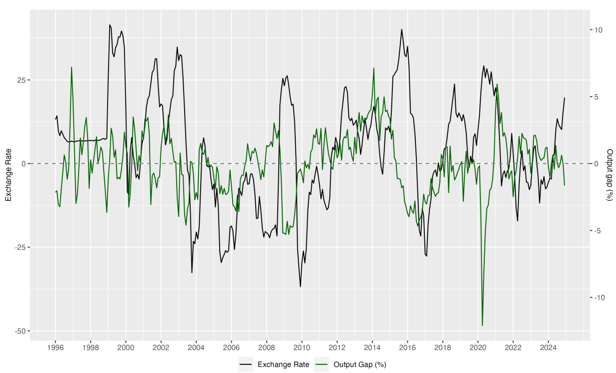
(a) Historical Development for ex and i



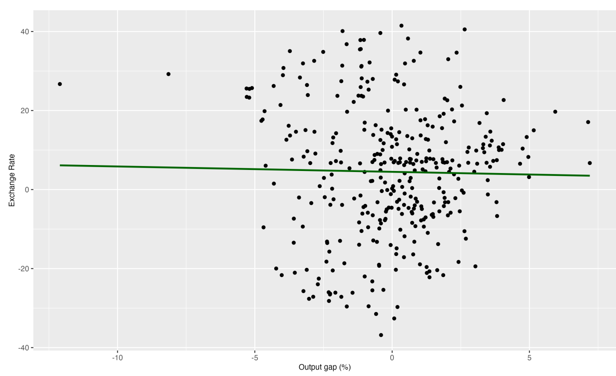
(b) Correlation Analysis for ex and i



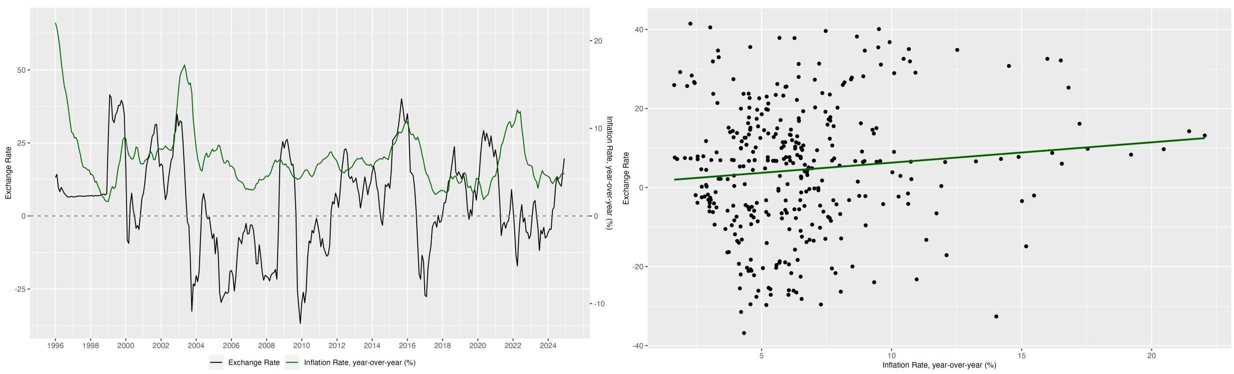
(c) Historical Development for ex and $\hat{y}$



(d) Correlation Analysis for ex and $\hat{y}$



(e) Historical Development for ex and π (f) Correlation Analysis for ex and π



Note: This figure presents the historical development and correlation between the exchange rate (ex) and three key macroeconomic variables: the monetary policy rate (i), output gap ($\hat{y}$), and inflation rate (π), over the period 1996M1–2024M12. For each variable pair their historical development is shown (left) as well as the correlation between the variables (right). Regression slope coefficients are 0.23 for $ex \sim i$, -0.14 for $ex \sim \hat{y}$, and 0.52 for $ex \sim \pi$.
Source: Own presentation of data collected from Banco Central do Brasil (2025a), Banco Central do Brasil (2025c), FRED (2025a), FRED (2025c), and FRED (2025d), compiled as indicated in Table 4.1 and processed in accordance with the methodology in Section 4.1.

The relationship between the exchange rate and the output gap appears to be mixed, with some periods exhibiting positive correlations and others exhibiting negative correlations. The negative correlations appear more pronounced, with large movements in the output gap being associated with large opposite movements in the exchange rate. These movements align with theory, which states that there exists a negative correlation between the output gap and exchange rates through the export channel. Furthermore, a floating exchange rate functions as a natural stabilization tool for the economy, according to the Mundell-Fleming model, at least for small open economies (Gottfries, 2013, pp. 398-399). These effects could be present to some degree in Brazil as well.

The relationship between the exchange rate and inflation also appears appears to vary, with some periods exhibiting positive correlations and others exhibiting negative correlations. On multiple occasions, large increases in inflation appear to be followed by large decreases in the exchange rate. However, several periods exhibit positive correlations, such as approximately 2003, 2008–2009, and 2014–2016. The first increase in inflation is partly linked to a decrease in exchange rate depreciation, according to BCB, as per Section 2. The 2008–2009 period corresponds to the global financial crisis, which was preceded by a positive output gap driven by strong domestic and international demand. This surge in demand contributed to upward pressure on the exchange rate and rising inflation. The period from 2014 to 2017 was characterized by stagflation, primarily driven by commodity prices (ECB, 2016). The theoretical relationship suggests that an increase in inflation would depreciate the currency, as higher inflation reduces the real interest rate, assuming other factors, such as demand, do not increase simultaneously.

The exchange rate is influenced by interest rates, where an increase typically leads to an appreciation of the currency, as outlined in Section 3. However, the exchange rate is also affected by other global factors, including foreign inflation and interest rates, as well as domestic inflation and interest rates (Gottfries, 2013, p. 379 & p. 388).

The correlation shown in Figures 4.5d, 4.5d and 4.5f reveals distinct relationships. The correlation between monetary policy rate and the exchange rate shows a positive correlation, with a slope of 0.23. Meanwhile, the correlation between the exchange rate and output gap indicates a negative correlation, with a slope of -0.14, while the correlation between inflation and the exchange rate shows a positive correlation, with a slope of 0.52. The correlation analysis corresponds with the theoretical predictions. However, several events over the period may have influenced these correlations, such as COVID-19, the global inflation surge in 2022, the period of stagflation, and other economic disruptions.

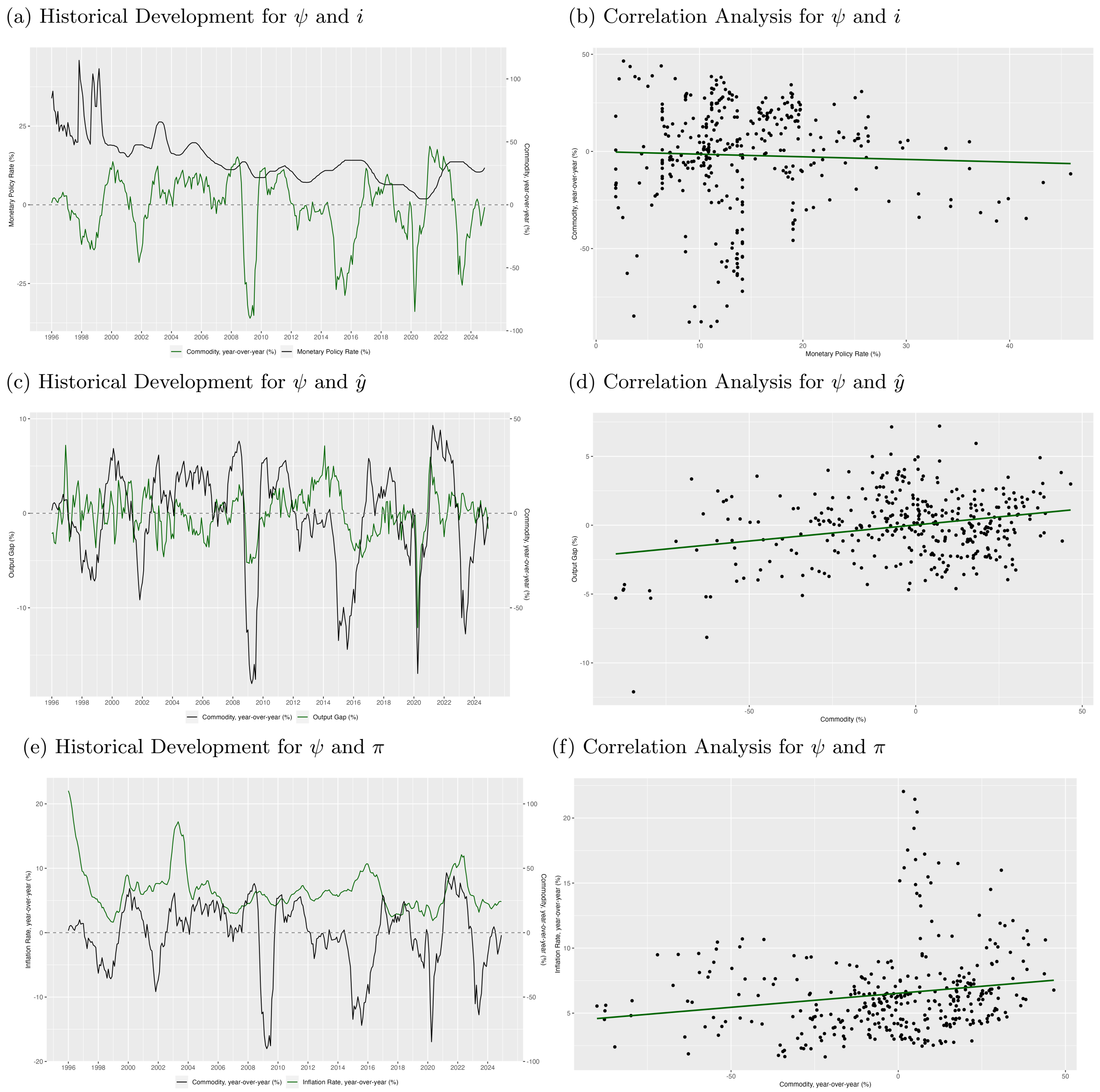
These findings indicate that an increase in the output gap would lead to an appreciation of the domestic currency, while an increase in inflation would result in its depreciation. An increase in the monetary policy rate would result in appreciation. However, it is not possible to determine precisely how the variables influence each other. Therefore, the results also suggest that a depreciation would decrease inflation, while an appreciation of the currency could lead to an increase in the output gap and the monetary policy rate. A more in-depth analysis is needed.

4.2.5. Commodity Prices, Monetary Policy Rate, Output Gap and Inflation Rate

Figures 4.6a, 4.6e, and 4.6f illustrate the historical evolution of commodity prices, the monetary policy rate, output gap, and inflation rate from 1996 to 2024.

The relationship between commodity prices and the monetary policy rate is ambiguous. In some periods, rising commodity prices coincide with interest rate hikes, consistent with central banks responding to inflationary pressures. In commodity-exporting economies such as Brazil, higher global prices increase export revenues and domestic demand. However, if production inputs also become more expensive, the net effect on aggregate demand becomes uncertain. Conversely, declining commodity prices may dampen both demand and inflation, prompting monetary easing. As commodity price shocks originate externally, they represent transmission mechanisms largely outside the central bank's control. Nevertheless, not all periods support the expected positive correlation. For example, between 2015 and 2017, Brazil experienced stagflation despite falling commodity prices. Similarly, during the global financial crisis, both commodity prices and interest rates declined. In addition, the long-term downward trend in interest rates over the sample period may have distorted this relationship.

Figure 4.6: Commodity Prices, Output Gap and Inflation, 1996M1-2024M12



Note This figure presents the historical development and correlation between the commodity prices (ψ) and three key macroeconomic variables: the monetary policy rate (i), output gap ($\hat{y}$), and inflation rate (π), over the period 1996M1–2024M12. For each variable pair their historical development is shown (left) as well as the correlation between the variables (right). Regression slope coefficients are -0.13 for $\psi \sim i$, 0.02 for $\psi \sim \hat{y}$, and 0.02 for $\psi \sim \pi$.
Source: Own presentation of data collected from Banco Central do Brasil (2025a), Banco Central do Brasil (2025c), FRED (2025c), FRED (2025d), FRED (2025e), and World Bank Group (2025), compiled as indicated in Table 4.1 and processed in accordance with the methodology in Section 4.1.

The correlation between commodity prices and the output gap appears mixed - positive in some periods, negative in others. However, during key episodes such as 2009, 2015–2017, and early 2020, the relationship was largely positive. T his pattern aligns with economic theory: as a major commodity exporter, Brazil tends to benefit from rising commodity prices through increased income, while price declines reduce revenues and can trigger downturns, as observed during the 2015–2017 crisis (Cuevas et al., 2018, pp. 16–26).

The relationship between inflation and commodity prices also appears mostly positive, though exceptions exist - most notably during the stagflation episode of 2015–2017. As outlined in Section 3, commodity prices represent an external factor beyond the central bank's control, but one that influences inflation through both cost and demand channels. On the cost side, higher commodity prices raise input costs, producing cost-push inflation. On the demand side, especially in economies like Brazil, higher export revenues increase domestic consumption and investment. Additionally, rising commodity prices may lead to greater asset acquisition by producers, which can further intensify inflationary pressures. This inflationary effect, however, can be partially offset by tighter monetary policy. As Drechsel et al. (2019) suggests, central banks in small open economies may mitigate overheating during commodity booms through pre-emptive interest rate hikes. Thus, increases in commodity prices contribute to inflation both directly through input costs, and indirectly through stronger domestic demand and wealth effects.

Figure 4.6b shows a weak negative correlation between commodity prices and the monetary policy rate of -0.13, which runs counter to theoretical expectations. Correlations in Figures 4.6f and 4.6d also provide only limited support: the correlation between commodity prices and the output gap is 0.02, and that between commodity prices and inflation is also 0.02. While these values align in direction with theory, their low magnitudes suggest that structural breaks, exogenous shocks (e.g., COVID-19), or long-run trends (e.g., declining interest rates) may obscure the true relationships.

The observed negative correlation between the monetary policy rate and commodity prices may reflect the long-term downward trend in interest rates rather than a causal relationship. Overall, while descriptive evidence suggests that increases in commodity prices are associated with rising output and inflation, the weak correlations underscore the need for a more rigorous empirical framework to draw robust conclusions.

4.2.6. Partial Conclusion

The observed relationships among the variables largely align with theoretical expectations. Higher interest rates tended to coincide with lower output, reflecting the countercyclical stance of monetary policy. Exchange rate dynamics also aligned with open-economy theory: during large movements in one variable, the other variables typically moved in the opposite direction. However, the overall correlation between these variables remains negative. Commodity price fluctuations had similarly expected effects on a commodity-exporting economy. Price booms fuelled economic growth but also induced higher inflation. Rising commodity prices appear to have contributed to inflationary pressures through both cost-push and demand channels.

Some findings diverged from theoretical expectations. The simple correlation analysis in Figure 4.3 shows a positive correlation between the monetary policy rate and inflation, which contradicts the expectation that an increase in interest rates would lower inflation. This paradox may reflect the endogeneity of policy: rising inflation prompts the central bank to hike the monetary policy rate, leading to a pattern where high inflation periods coincide with high monetary policy rate periods. Furthermore, the output-inflation relationship, which is established through the Phillips curve, has not been uniformly inverse. For example, the period from 2015 to 2017 was characterized by stagflation.

The output-inflation relationship exhibits mixed tendencies, with some large movements being negatively related, resulting in a negative correlation. This proposed relationship does not align with theoretical expectations. Importantly, the descriptive analysis has clear limitations in capturing the true dynamics between the variables. Simple correlations and historical trends do not account for causality or accurately reflect the underlying relationships. Furthermore, the strength of the correlation across the period is not uniform, indicating that multiple factors may influence the relationship. Thus, the descriptive statistics do not provide results that fully capture the depth of interactions between the variables. To better understand this relationship, the analysis is extended to incorporate a time-dependent approach to assess the effectiveness of monetary policy.

To better capture the evolving relationships among these macroeconomic variables, the thesis now turns to the TVP-SVAR-SV framework in Section 5. This time-varying econometric approach allows for a more nuanced analysis of how monetary policy effectiveness changes across different economic environments.

5. Econometric Methodology

This section outlines the econometric methodology adopted in the thesis, with a particular focus on the rationale for selecting the Time-Varying Parameter Structural Vector Autoregressive model with Stochastic Volatility (TVP-SVAR-SV). It begins with a targeted review of empirical studies that evaluate the effectiveness of monetary policy, highlighting the limitations of traditional VAR approaches and motivating the use of time-varying models. The discussion then turns to the estimation method, introducing the key principles of Bayesian inference and detailing the specific implementation of the TVP-SVAR-SV model, including the choice of priors, the causal ordering of variables, lag selection, and diagnostic testing.

5.1. Motivation and Related Literature

A central question in macroeconomics is how effectively monetary policy can stabilize output and inflation, particularly during times of economic distress. This effectiveness is often assessed through empirical measures such as IRFs from structural VAR models, or through summary indicators like the sacrifice ratio - the amount of output lost in the pursuit of lower inflation (Cecchetti & Rich, 2001, pp. 7-10). These metrics provide insight into how economies respond to monetary interventions, and how such responses vary across different structural contexts.

A broad body of literature has examined the effectiveness of monetary policy across countries and time periods. For advanced economies, evidence generally shows that monetary policy can play a stabilizing role, though its impact is not uniform. For instance, Bouis et al. (2013) finds that while monetary policy helped avert deflation during the global financial crisis, its ability to stimulate output was limited due to low natural interest rates, fiscal consolidation, and weakened credit channels. Similarly, Aastveit et al. (2017) shows that economic uncertainty significantly dampens the effect of monetary policy on output and investment in the United States, particularly during periods of heightened market volatility. These findings highlight that institutional, financial, and macroeconomic conditions can all shape the transmission and effectiveness of policy.

Turning to Brazil, the literature has focused on understanding how the country's economic structure and institutional changes have influenced the role of monetary policy. Minella (2003) investigates the real effects of monetary policy across three distinct inflation regimes between 1975 and 2000. The results show that while monetary shocks affected output consistently, their impact on inflation only became significant in the post-1994 period, reflecting institutional improvements in Brazil's monetary framework. More recently, Araujo et al. (2022) applies a Markov-Switching VAR model to data from 1996 to 2020 and finds that both monetary and fiscal policies have stronger effects during recessions than in normal times - supporting the view that active countercyclical policy can mitigate downturns.

Despite these contributions, most studies on Brazil rely on static or regime-switching VAR models that assume discrete changes in the economic environment. These approaches may fail to capture the gradual and continuous evolution of monetary policy transmission mechanisms driven by financial liberalization, changes in central bank credibility, or external shocks. For example, reforms in inflation targeting and capital flow management during the 2000s likely shifted the way monetary policy operates in Brazil, but standard models may miss these dynamics.

To address these limitations, recent studies have turned to models with time-varying parameters and stochastic volatility, specifically the TVP-SVAR-SV model. For instance, Lü et al. (2024) employs such a framework to study China and finds that policy transmission efficiency, measured by the responsiveness of market rates to changes in the policy rate, improved significantly after 2015, reflecting institutional and financial reforms. The TVP-SVAR-SV model is particularly well-suited for macroeconomic environments where structural shifts occur gradually and policy effects are not constant over time. This thesis builds on that approach by applying a TVP-SVAR-SV model to Brazil.

5.1.1. Model Selection

The TVP-SVAR-SV model has been chosen for the analysis due to its ability to capture the time-varying nature of macroeconomic relationships. This follows as the flexibility of the TVP-SVAR-SV model accommodates both time-varying coefficients and stochastic volatility, which makes it particularly well-suited for analysing the dynamic and often non-linear interactions between economic variables. For instance, the unemployment rate increases more rapidly at the beginning of a recession than it decreases once a recovery begins, while financial markets often are characterized by volatility clusters. These examples of nonlinearity can stem from different underlying structures in the data series, which the TVP-SVAR-SV approach is able to capture by modelling the relationships between variables as evolving over time. Hence, the TVP-SVAR-SV model is highly appropriate in a macroeconomic context where shifts in structural dynamics, policy changes, and external shocks can alter the behaviour of variables (Lubik & Matthes, 2015, pp. 323-324). By allowing the model's parameters to evolve according to a random walk process, the TVP-SVAR-SV framework accounts for both temporary and permanent changes in these relationships, providing a more accurate and flexible representation of the underlying economic processes (Bekiros & Paccagnini, 2013, pp. 637-638). In addition to the time-varying coefficients, the inclusion of stochastic volatility in the model allows for the variances of the error terms to change over time, further enhancing its ability to capture the dynamic properties of macroeconomic time series (Lubik & Matthes, 2015, pp. 323-324). The TVP-SVAR-SV model's ability to incorporate both time-varying parameters and stochastic volatility relaxes the stationarity assumptions of a traditional VAR model (Bekiros & Paccagnini, 2013, pp. 637-638) and allows it to model the nonlinearities observed in many macroeconomic variables. Hence, the model offers a more nuanced representation of economic dynamics relative to more traditional VAR models (Lubik & Matthes, 2015, pp. 323-324).

On the other hand, the estimation of a TVP-SVAR-SV model presents its own set of challenges due to the amount of parameters which need to be estimated. Although it is possible to derive the likelihood analytically for the estimation problem, maximizing it over the high-dimensional parameter space of the model is often challenging, and hence frequentists approaches like Maximum Likelihood Estimation (MLE) of a TVP-SVAR-SV model is highly inefficient. Instead, Bayesian methods provide a more suitable framework for estimation (Bekiros & Paccagnini, 2013, pp. 637-638). The following section outlines the principles of Bayesian inference and its application to the estimation of TVP-SVAR-SV models.

5.2. Introduction to Bayesian Inference

This section introduces Bayesian inference, providing foundational insights into Bayesian statistics before applying it to the estimation of the TVP-SVAR-SV model. Bayesian inference is based on Bayes' theorem, which describes how prior beliefs are updated in light of new evidence. This contrasts with the frequentist approach, which views probability as a measure of long-run frequencies in repeated samples and focuses on hypothesis testing, confidence intervals, and p-values.

A key distinction between these two approaches lies in how they interpret probability. Frequentist statistics assigns probabilities to data rather than to hypothesis, relying on p-values to determine the likelihood of obtaining a sample at least as extreme as the observed one, assuming the null hypothesis is true. For example, the probability of flipping heads in a fair coin toss is 50% because, over infinite trials, heads occurs half the time. Bayesian statistics, on the other hand, treats probability as a degree of belief that can be updated as new evidence emerges. If one suspects a coin is biased and observes several heads in a row, their belief about the coin's fairness is adjusted accordingly.

This ability to incorporate prior knowledge is a defining feature of Bayesian inference. Instead of producing single point estimates, Bayesian methods generate probability distributions for parameters, reflecting uncertainty and allowing for continuous updates to the distributions as new data becomes available. This process follows directly from Bayes' theorem, which is mathematically expressed as:

$$P(A|B) = \frac{P(B|A) \times P(A)}{P(B)} \tag{5.1}$$

where $P(A)$ is the prior probability, representing initial beliefs about event A before observing the data, $P(B|A)$

is the likelihood, describing the probability of observing data B given that A is true, $P(B)$ is the marginal probability, ensuring proper normalization, and $P(A|B)$ is the posterior probability, representing the updated belief about A after observing B.

A practical example of Bayesian inference is medical testing. Suppose a disease affects only 0.5% of the population, but a diagnostic test has a 98% accuracy rate for both positive and negative results. In a frequentist framework, a positive test result would often be interpreted as meaning the person has a 98% chance of having the disease, since the test is 98% accurate. However, this interpretation ignores prior probabilities - specifically, how rare the disease is in the general population. In contrast, the Bayesian approach incorporates this prior information when updating beliefs which can be seen when applying Bayes' theorem:

$$P(A|B) = \frac{0.98 \times 0.005}{(0.98 \times 0.005) + (0.02 \times 0.995)} \approx 0.198 \tag{5.2}$$

This result shows that despite the test's high accuracy, the probability of actually having the disease given a positive result is only about 19.8%, due to the disease's rarity. However, if the individual takes an independent second test and tests positive again, the updated probability rises significantly:

$$P(A|B) = \frac{0.98 \times 0.198}{(0.98 \times 0.198) + (0.02 \times (1 - 0.198))} \approx 0.923 \tag{5.3}$$

After a second positive test, the probability of actually having the disease increases to approximately 92.3%. This example illustrates how Bayesian inference allows for continuous updating of probabilities as new information becomes available.

By continuously updating beliefs as new data become available, Bayesian inference provides a flexible and intuitive framework for statistical estimation. However, a challenge in Bayesian statistics is determining the prior probability, as it can sometimes be subjective or based on limited information (Fornacon-Wood et al., 2021, pp. 1076-1077). Despite this, Bayesian methods are particularly well-suited for estimating models with large parameter spaces and latent structures, such as the TVP-SVAR-SV model employed in this thesis, where they enhance estimation efficiency and accommodate uncertainty in a principled way (Bekiros & Paccagnini, 2013, pp. 637–638).

The following section applies these Bayesian principles to the specific context of this thesis by presenting the structure and estimation procedure of the TVP-SVAR-SV model.

5.3. Time-Varying Parameter SVAR with Stochastic Volatility

Building on the Bayesian estimation approach, this section introduces the structure and estimation of the TVP-SVAR-SV model following the methodology applied in Primiceri (2005) with the modifications presented in Negro & Primiceri (2014).

As previously mentioned, the primary advantage of this model lies in its ability to capture evolving relationships between economic variables over time. Unlike the traditional VAR models, which assume constant parameters, the TVP-SVAR-SV framework allows for time-varying coefficients, meaning that both temporary fluctuations and structural changes can be accounted for. An additional feature of the model is the inclusion of stochastic volatility, which is beneficial for macroeconomic analysis. Many economic variables exhibit periods of high or low volatility, often clustering around economic crises or policy changes. Ignoring such variation and assuming constant volatility may lead to model misspecification and biased estimates. By incorporating stochastic volatility, the TVP-SVAR-SV model accounts for these shifts, improving its ability to capture the true underlying dynamics of economic shocks. Despite these advantages, estimating the model presents significant challenges. The likelihood function of a TVP-SVAR-SV model is highly complex, making frequentist estimation techniques impractical. Instead, Bayesian methods, specifically Markov Chain Monte Carlo (MCMC) estimation, offer a more robust method for efficiently handling the high-dimensional parameter space (Nakajima, 2011).

The TVP-SVAR-SV model is defined as:

$$y_t = c_t + B_1 y_{t-1} + ... + B_{k,t} y_{t-k} + u_t, \quad t = 1, \dots, T \tag{5.4}$$

where y_t denotes an $n \times 1$ vector of observed endogenous variables, c_t is an $n \times 1$ vector of time-varying intercepts, $B_{i,t} = 1, .., k$ represents an $n \times n$ matrix of time varying coefficients, and u_t is an $n \times 1$ vector the structural shocks, which are heteroscedastic and follow a stochastic volatility process, with the variance-covariance matrix Ω_t.

To ensure identification, the variance-covariance matrix Ω_t is decomposed using a triangular reduction:

$$A_t \Omega_t A_t' = \Sigma_t \Sigma_t' \tag{5.5}$$

where A_t refers to a lower triangular matrix, capturing time-varying contemporaneous relationships between variables, expressed as:

$$A_t = \begin{bmatrix} 1 & 0 & \cdots & 0 \\ \alpha_{21,t} & 1 & \cdots & \vdots \\ \vdots & \vdots & \ddots & 0 \\ \alpha_{n1,t} & \cdots & \alpha_{nn,t} & 1 \end{bmatrix} \tag{5.6}$$

Meanwhile, Σ_t is a diagonal matrix which captures the time-varying volatilities and is given by:

$$\Sigma_t = \begin{bmatrix} \sigma_{1,t} & 0 & \cdots & 0 \\ 0 & \sigma_{2,t} & \cdots & \vdots \\ \vdots & \vdots & \ddots & 0 \\ 0 & \cdots & 0 & \sigma_{n,t} \end{bmatrix} \tag{5.7}$$

where $\sigma_{i,t}$ denotes the standard deviation of structural shocks for variable i at time t.

Using this decomposition, the TVP-SVAR-SV model can be rewritten as:

$$y_t = c_t + B_1 y_{t-1} + ... + B_{k,t} y_{t-k} + A_t^{-1} \Sigma_t \varepsilon_t, \quad \varepsilon_t \sim \mathrm{N}(0, \Sigma_t) \tag{5.8}$$

$$V(\varepsilon_t) = I_n \tag{5.9}$$

where ε_t represents a vector of white noise shocks, whose variance-covariance matrix is an identity matrix for the n variables in the system as stated by Equation 5.9. This ensures that the structural shocks are standardized.

To simplify the notation, all coefficients can be stacked into a single time-varying coefficient matrix B_t, allowing Equation 5.8 to be rewritten as:

$$y_t = X_t' B_t + A_t^{-1} \Sigma_t \varepsilon_t, \quad \varepsilon_t \sim \mathrm{N}(0, \Sigma_t) \tag{5.10}$$

$$X_t' = I_n \otimes [1, y_{t-1}', \cdots, y_{t-k}'] \tag{5.11}$$

Here, $\otimes$ denotes the Kronecker product.

Furthermore, letting α_t represent the non-zero and non-one elements of A_t, and letting σ_t denote the diagonal elements of Σ_t, the time-varying parameters can be modelled. This leads to the following time-varying specifications for the model parameters:

$$B_t = B_{t-1} + \upsilon_t \tag{5.12}$$

$$\alpha_t = \alpha_{t-1} + \zeta_t \tag{5.13}$$

$$\log\sigma_t = \log\sigma_{t-1} + \eta_t \tag{5.14}$$

Here, B_t and α_t evolve according to random walks, while σ_t follows a geometric random walk[1], placing it within the framework of stochastic volatility models, where variance is driven by latent components. The random walk assumption suggests that variables could eventually reach upper or lower bounds, but since the equations are considered over a finite time horizon, this does not pose a practical issue. The use of random walks allows the model to focus on capturing permanent shifts in the parameters while reducing the number

[1]The geometric random walk models percentage changes rather than absolute changes, unlike the traditional random walk. This ensures that the predicted value cannot go negative (Sabir & Santhanam, 2014). As a result, the geometric random walk is ideal for modelling the stochastic volatility which cannot take negative values.

of parameters that need to be estimated (Primiceri, 2005, pp. 823-825). As B_t, α_t and $\log\sigma_t$ are latent variables, they must be estimated using state-space models[2] (Feng et al., 2019, p. 1).

In terms of the variance-covariance structure of the shocks, the model assumes a joint normal distribution, with the variance-covariance matrix represented by:

$$V = Var\left(\begin{bmatrix} \varepsilon_t \\ \upsilon_t \\ \zeta_t \\ \eta_t \end{bmatrix}\right) = \begin{bmatrix} I_n & 0 & 0 & 0 \\ 0 & Q & 0 & 0 \\ 0 & 0 & S & 0 \\ 0 & 0 & 0 & W \end{bmatrix} \tag{5.15}$$

where I_n is an identity matrix of n dimensions, while Q, S, and W are positive definite matrices[3]. The restrictions imposed in Equation 5.15 are not strictly necessary but are introduced for practical reasons. Without the zero restrictions, shocks could become correlated, which would require the use of priors and increase the number of parameters. Furthermore, with Q and W being diagonal and S being block diagonal, where each block contains parameters belonging to different equations, the contemporaneous relationships among the variables can evolve independently. This structure simplifies the inference process and enhances the efficiency of the estimation (Primiceri, 2005, pp. 823-825 & p. 846).

5.3.1. Estimation Method

Given the presence of time-varying parameters, stochastic volatility, and latent variables, estimating the TVP-SVAR-SV model requires a method capable of efficiently handling both high dimensionality and non-linearity. Frequentist estimation techniques like Ordinary Least Squares (OLS) and MLE are not suited due to these complexities. This follows as OLS cannot handle the inclusion of latent variables, while MLE has a tendency to shrink variance estimates toward zero in high-dimensional settings due to its reliance on likelihood estimation. MLE often fails to properly account for uncertainty when dealing with hierarchical or latent variable models, leading to biased estimates. Moreover, MLE could potentially get stuck in either a local minimum or maximum due to the degree of non-linearity and high dimensionality, consequently resulting in a non-optional solution. Instead, a Bayesian approach is employed to estimate the posterior distributions of the parameters. Specifically, MCMC methods, and in particular the Gibbs sampler, are used to iteratively approximate the posterior distributions of the variables B^T, A^T, Σ^T, and the hyperparameters of the variance-covariance matrices Q, S and W. Gibbs sampling facilitates estimation by sequentially sampling from the conditional dis-

[2] State-space models operate through an iterative prediction and updating process, where each time step refines the estimates, ultimately yielding posterior values (Stoffer, 2017, 287-295).

[3] A positive definite matrix is one that is symmetric and has only positive eigenvalues, $\lambda > 0$, implying it is invertible with $\det > 0$ (Nicholson, 2019, p. 434).

tributions of each parameter, reducing the complexity of the high-dimensional problem and ensuring convergence to the joint posterior distribution (Primiceri, 2005, pp. 825-826). A detailed explanation of the MCMC process and the workings of a generic Gibbs sampler can be found in Appendix B.1.

As mentioned, Gibbs sampling divides the estimation process into smaller segments, also known as blocks, to improve the computational efficiency. Specifically for the TVP-SVAR-SV model, the first block focuses on deriving Σ^T, using all available data up to time T, denoted as y^T, the history of the coefficients $\theta \equiv [B^T, A^T, V]$ (Primiceri, 2005, pp. 825-828 & Negro & Primiceri, 2014, pp. 1-5), and a mixture of indicators s^T, which select the component of the mixture for each variable at each date. These mixture indicators correspond to latent state variables that determine which component of a mixture-of-normals approximation best represents the distribution of shocks at each time point (Shalizi, 2009). Consequently, the first step in the Gibbs sampling procedure for the TVP-SVAR-SV model can be expressed as follows:

$$\text{Step 1: } \tilde{p}(\Sigma^T | y^T, \theta, s^T) \tag{5.16}$$

Once Σ^T is estimated, the second block proceeds by estimating the posterior distribution of (θ, s^T) conditional on y^T and Σ^T. This is done through two sequential steps: first estimating θ and then obtaining s^T:

$$\text{Step 2: } \tilde{p}(\theta, s^T | y^T, \Sigma^T) \tag{5.17}$$

$$\text{Step 2.1: } p(\theta | y^T, \Sigma^T) \tag{5.18}$$

$$\text{Step 2.2: } \tilde{p}(s^T | y^T, \Sigma^T, \theta) \tag{5.19}$$

Here, the notation ˜ indicates the use of an auxiliary approximating model that uses historical volatility patterns to enhance estimation efficiency[4] (Primiceri, 2005, pp. 825-828 & Negro & Primiceri, 2014, pp. 1-5).

For practical implementation in this thesis, the estimation of the TVP-SVAR-SV model is carried out using the `bvarsv` package in R, which follows the methodology outlined in Primiceri (2005), incorporating subsequent corrections from Negro & Primiceri (2014). The `bvarsv` package is optimized with C++ to handle the computational intensity of the MCMC algorithm efficiently and includes built-in tools for conducting impulse response analysis (Krüger, 2015, p. 1).

5.3.2. Selection of Priors

Before to estimating the TVP-SVAR-SV model, the prior values and their corresponding distributions must be defined. These initial values serve as the starting point for obtaining posterior estimates, as outlined in Section 5.2. Overall, the selected of prior values follows the procedure described in Primiceri (2005).

[4]The auxiliary model is introduced because directly sampling from the exact posterior can be computationally challenging due to the complex dependence structure in the stochastic volatility framework (Fornari & Mele, 2006).

For the time-varying coefficients, $p(B_0)$, simultaneous relations, $p(\alpha_0)$, and the log standard error, $p(\log\sigma_0)$, the priors are derived as point estimates from a time-invariant SVAR model with the same causal ordering and lag selection as specified in Section 5.3.3. This SVAR model is estimated using OLS over the period 1996M1 to 1999M12, with the TVP-SVAR-SV model applied to the subsequent period from 2000M1 to 2024M12. The priors for A_0 and B_0 are set to the mean of the time-invariant SVAR, with their variance being four times the variance of the time-invariant SVAR. The mean of the distribution of $\log\sigma$ is set to be the point estimate of the standard errors from the time-invariant SVAR, while the variance-covariance matrix for ε_t is initialized as an identity matrix.

The initial states for the covariance, log volatilities, and hyperparameters are assumed to be independent of one another. The priors for the hyperparameters Q, W, and S are modelled using an inverse-Wishart distribution. The degrees of freedom for the hyperparameters are set as follows: W is assigned four degrees of freedom, and S has two and three degrees of freedom for its respective blocks. For Q, the degrees of freedom are set equal to the number of observations in the initial subsample of the time-invariant SVAR, corresponding to 48. The priors for k_Q and k_S are set to be values of 0.1, which corresponds to weakly informative priors, also known as diffuse priors. These priors are not meant to impose strong beliefs or expectations about the parameters before observing the data. Instead, they allow the data to primarily drive the estimation of these parameters. This approach is recommended by Primiceri (2005, pp. 830-831).

This setup implies that the prior for the TVP-SVAR-SV model are anchored in the time-invariant SVAR. The burn-in period is set to 5,000 iterations, meaning that the first 5,000 iterations of the Gibbs sampler are discarded to allow the Markow chain to converge to a stationary distribution. Moreover, an additional 200,000 iterations are made, with a thinning factor of 40, implying that only every fortieth iteration is kept in order to improve the computational efficiency and reduce any potential autocorrelation among the MCMC chains. This results in a total of 5,000 saved iterations used to estimate the parameter distribution of each of the parameters of the TVP-SVAR-SV model at every point in time (Krüger, 2022, pp. 3-5 & Lai, 2019).

With the priors and estimation setup established, the next step is to identify the structural shocks within the system. This requires specifying a causal ordering of variables and selecting an appropriate lag structure, as discussed below.

5.3.3. Causal Ordering of Variables and Lag Selection

To interpret the effects of different shocks in the system, the model requires structural identification. Without it, the reduced-form residuals would mix together different sources of economic shocks, making it difficult to draw clear conclusions. In this model, identification is achieved by imposing a recursive structure through a

Cholesky decomposition on the contemporaneous relationships between variables. This allows the model to distinguish between structural shocks and estimate their time-varying impact (Primiceri, 2005).

The recursive identification scheme follows the ordering: commodity prices (ψ_t), monetary policy rate (i_t), exchange rate (ex_t), inflation rate (π_t), and output gap ($\hat{y}_t$). This ordering is motivated by both theoretical considerations and the empirical objective of the thesis - namely, to quantify and compare the contribution of the exchange rate and commodity price channels in the transmission of monetary policy over time. Thus the contemporaneous matrix A_t is specified as:

$$A_t \left(\begin{bmatrix} \psi_t \\ i_t \\ ex_t \\ \pi_t \\ \hat{y}_t \end{bmatrix} \right) = \begin{bmatrix} 1 & 0 & 0 & 0 & 0 \\ \alpha_{21,t} & 1 & 0 & 0 & 0 \\ \alpha_{31,t} & \alpha_{32,t} & 1 & 0 & 0 \\ \alpha_{41,t} & \alpha_{42,t} & \alpha_{43,t} & 1 & 0 \\ \alpha_{51,t} & \alpha_{52,t} & \alpha_{53,t} & \alpha_{54,t} & 1 \end{bmatrix} \tag{5.20}$$

Commodity prices are placed first under the assumption that they are determined largely by global supply and demand conditions, which are exogenous to the Brazilian economy and not affected by domestic macroeconomic developments within the same month. As Brazil is a price taker in global commodity markets, this variable is treated as contemporaneously exogenous.

The monetary policy rate is ordered second, implying that the central bank observes global commodity price conditions but does not react within the same month to contemporaneous changes in domestic macroeconomic indicators such as inflation, output, or the exchange rate. This reflects information and decision lags typical of monetary policy, especially at the monthly frequency. This follows the argument made by Kim & Roubini (2005) and is widely adopted in empirical macroeconomic research.

The exchange rate is ordered third, allowing it to respond contemporaneously to both global commodity shocks and monetary policy decisions. This reflects the high-frequency nature of exchange rate adjustments in financially open economies such as Brazil. Notably, Brazil operates under a floating exchange rate regime, and capital flows are sensitive to interest rate changes and external shocks - thus justifying its placement after the monetary policy rate.

Inflation is placed fourth, allowing it to respond contemporaneously to commodity prices, monetary policy rate, and exchange rate movements, but not to changes in output. This captures the idea that price levels may react quickly to cost-push factors, such as import prices influenced by exchange rate fluctuations, but still exhibit nominal rigidities that delay full adjustment to real economic activity.

Finally, the output gap is ordered last. It is assumed to react contemporaneously to all other variables, including inflation and the monetary policy rate. This reflects the relative flexibility of real activity to respond to shocks, while also allowing the model to capture delayed effects of policy and external conditions on output.

This ordering also supports the thesis's core identification strategy: by including both exchange rate and commodity prices in the baseline model, and systematically excluding them in alternative specifications, it is possible to isolate and measure the contribution of each external channel to the transmission of monetary policy. The structure ensures that the baseline impulse responses account for the full transmission mechanism, while the changes in responses under the restricted models reflect the exclusion of a specific channel - thereby enabling a meaningful analysis of the policy trade-off faced by monetary authorities over time.

Moreover, an alternative identification order is examined in Appendix E in which the order of the inflation rate and output gap is reversed. This allows for an assessment of how sensitive the findings in the thesis is to this specific identification ordering.

To estimate, TVP-SVAR-SV, it is important to make a strategic decision on the number of lags in the process. While it is common in the literature to use two lags for a TVP-SVAR-SV model (Lubik & Matthes, 2015, pp. 345), this thesis will use one lag as the number of the variables included in this TVP-SVAR-SV model is larger than the usual TVP-SVAR-SV models, which means that the model has relatively more parameters that needs to be estimated. Primiceri (2005) uses three variables where this thesis uses five, which extensively increases the computational effort needed as the number of parameters needed to be estimated increase exponentially as more variables are added. To limit the computational power needed to estimate the model, a standard-scaler[5] is applied to reduce the magnitude of the variables and the number of lags is decreased to one to reduce the number of parameters as recommended by the developer of the of the `bsvarsv` package (Krüger, 2017).

With the model specification complete and estimation strategy implemented, the next step is to evaluate the reliability and validity of the results through a series of diagnostic checks.

5.4. Diagnostics

This section presents the econometric methodology employed for the diagnostic tests applied to the TVP-VAR-SV models estimated through MCMC methods, along with the results obtained. The reliability and robustness of the baseline model as well as the two alternative models excluding exchange and commodity

[5]This normalizes each variable such that it has a zero mean and a variance of one (Bergmeir, n.d.).

prices, respectively, have been evaluated by estimating the Effective Sample Size (ESS) and conducting Geweke's convergence diagnostic test for each the three model specification.

5.4.1. Effective Sample Size

The ESS is a key metric in MCMC estimation, used to evaluate the quality and reliability of a sample sequence. It quantifies the independent information contained in an autocorrelated sample, adjusting for the loss of information that results from correlations between successive samples (Stan Development Team, n.d., pp. 184-185).

In a scenario where the sample is free of autocorrelation, the raw sample size, N, directly reflects the amount of information available (Plummer et al., 2024, pp. 12-13). However, when autocorrelation is present, the true independent information within the sample decreases. As a result, the ESS provides an estimate of the number of independent samples that would offer the same level of statistical power as the autocorrelated sequence, denoted as N_{eff} (Stan Development Team, n.d., pp. 184-185). Essentially, the ESS represents the equivalent number of independent samples that would result in the same standard error as a set of correlated MCMC samples (Roy, 2020, pp. 392-393). In the absence of autocorrelation, the raw sample size and the effective sample size would be identical, i.e., $N = N_{\text{eff}}$ (Plummer et al., 2024, pp. 12-13).

To assess the reliability of the MCMC chains in the estimated model, the ESS is computed for each sample of the estimated parameters (Plummer et al., 2024, pp. 12-13). In the case of the TVP-VAR-SV model, this involves estimating the ESS for all components of the time-varying parameters outlined in Equations 5.12-5.14.

The models estimated in this thesis rely on 5,000 posterior draws per parameter. In an ideal setting where the Markov chains are fully efficient, that is, absent of any autocorrelation, this would result in an ESS where $N_{\text{eff}} = 5,000$ for each parameter. However, due to the inherent autocorrelation in MCMC chains, the actual amount of independent information is typically lower. The ESS adjusts the raw sample size to reflect this reduction, thereby providing a more accurate measure of the reliability of posterior estimates (Stan Development Team, n.d., pp. 184–185).

To evaluate whether the effective sample size for each parameter is sufficiently large, this thesis adopts a benchmark range. Specifically, an ESS within ±500 of the ideal value (i.e., between 4,500 and 5,500) is considered acceptable. This tolerance allows for minor deviations from perfect mixing while still ensuring a high degree of confidence in the numerical precision of posterior summaries. Substantially lower ESS values may indicate poor chain mixing, high autocorrelation, or inadequate exploration of the parameter space, and would warrant further diagnostic evaluation or sampling adjustments.

Table 5.1 presents the ESS values for each estimated model, grouped into three parameter blocks: i) the B_t parameters, which capture the time-varying coefficients associated with lagged endogenous variables, ii) the A_t parameters, representing the contemporaneous relationships in the structural matrix, and iii) the Σ_t parameters, which capture the stochastic volatility dynamics in the diagonal elements of the time-varying variance-covariance matrix. For each of these groups, the fraction of N_{eff} values that fall within the acceptable range of 4,500–5,500 is calculated and displayed. For a full overview of the distribution of ESS for every single parameter, please refer to Appendix C.

Table 5.1: Effective Sample Size Results

Model	B_t	A_t	Σ_t	Total
Baseline Model	55.17%	40.73%	32.88%	44.37%
Model Excluding Exchange Rate	75.35%	36.28%	32.25%	53.35%
Model Excluding Commodity Prices	53.93%	61.22%	43.98%	51.18%

Note: The table reports the proportion of effective sample sizes (N_{eff}) falling within the acceptable range of 4,500–5,500 for each parameter group (B_t, A_t, and Σ_t) across the three estimated models. A higher proportion indicates more efficient sampling and lower autocorrelation in the MCMC chains. The "Total" column reflects the overall share of parameters meeting the threshold across all groups. Note that this is not a simple average of the group-level proportions, as each group contains a different number of parameters. In the baseline model, B_t comprises 9,000 parameters, A_t 3,000, and Σ_t 7,500. In the alternative specifications, the corresponding group sizes are 6,000, 1,800, and 4,800 parameters, respectively.
Source: Own presentation of data collected from Banco Central do Brasil (2025a), Banco Central do Brasil (2025c), FRED (2025a), FRED (2025c), FRED (2025d), FRED (2025e), and World Bank Group (2025), compiled as indicated in Table 4.1 and processed in accordance with the methodology in Section 5.

The results of the estimated ESS are shown in Table 5.1. As seen from the table, the proportion of parameters with acceptable ESS values is moderate overall, with notable variation across both parameter groups and model specifications. In the baseline model, only 44.37% of all parameters fall within the 4,500–5,500 threshold, with particularly low rates for the contemporaneous effects (40.73%) and volatility parameters (32.88%). The lagged coefficients, by contrast, exhibit relatively better performance at 55.17%.

Among the alternative specifications, the model excluding the exchange rate shows the highest overall efficiency, with 53.35% of parameters in the acceptable range. This improvement is primarily driven by better mixing of the B_t block (75.35%), though the A_t and Σ_t components remain similarly low. The model without commodity prices shows a more balanced distribution, with all parameter groups showing slightly higher proportions than in the baseline, yielding an overall ESS success rate of 51.18%.

Although these results suggest that sampling efficiency is suboptimal, particularly for A_t and Σ_t, they do not invalidate the reliability of the models. A substantial share of parameters still meet the ESS benchmark. Furthermore, the distribution of ESS values across parameter blocks in each model specification is not extreme enough to undermine the stability or interpretability of the posterior summaries, as illustrated in Appendix C. In addition, all chains passed the supplementary convergence diagnostics as presented in Section 5.4.2.

Taken together, these results suggest that while sampling efficiency could be improved, the estimates remain sufficiently robust for inference and interpretation.

5.4.2. Geweke's Convergence Diagnostic

Geweke (1992) introduced a convergence diagnostic for Markov chains designed to evaluate convergence to a stationary distribution. The test compares the means of two segments of a Markov chain - typically the first 10% and the last 50% of the chain (Roy, 2020, p. 394). If the samples are drawn from the stationary distribution of the chain, the means of these two segments should be approximately equal, a condition reflected by Geweke's statistic having an asymptotically standard normal distribution. The test statistic is computed as a standard Z-score, which is the difference between the means of the two segments of the chain, normalized by the estimated standard error (Plummer et al., 2024, pp. 16-17):

$$Z_n = \frac{\bar{g}_{n_A} - \bar{g}_{n_B}}{\sqrt{\widehat{S_g(0)}/n_A + \widehat{S_g(0)}/n_B}} \tag{5.21}$$

where $\bar{g}n_A$ and $\bar{g}n_B$ represent the averages of the first n_A iterations and the last n_B iterations of the chain, respectively, and $\widehat{S_g(0)}$ denotes the asymptotic variance of the entire set of iterations. This Z-score is calculated under the assumption that the two segments of the chain are independent. Consequently, the test accounts for autocorrelation in the samples by estimating the standard error based on the spectral density evaluated at zero. The spectral density at zero, which reflects the variance or power of the Markov chain at lag zero, is derived from the autocorrelation function and can be calculated by summing the autocorrelations across all lags (Plummer et al., 2024, pp. 33-34; Roy, 2020, p. 394).

The Z-score from Geweke's convergence diagnostic is computed separately for each parameter that has been estimated. These individual Z-scores are then compared to a critical value at 5% significance level given by a standard distribution of ± 1.96.

Table 5.2 presents the results of Geweke's convergence diagnostic for each estimated model, grouped into the three parameter blocks (B_t, A_t, and Σ_t). For each of these blocks, the table reports the fraction of parameters for which the Z-score from Geweke's convergence diagnostic falls within the 95% confidence interval (± 1.96), indicating no statistically significant difference between the early and late portions of the MCMC chains. For a full overview of the distribution of Z-scores from Geweke's convergence diagnostic for all parameters, please refer to Appendix C.

As shown in the table, convergence performance is moderate to strong across all three model specifications. The baseline model achieves an overall pass rate of 76.84%, with particularly solid results for A_t (82.60%)

and Σ_t (78.44%), while B_t lags slightly at 73.59%. The two alternative models show improved convergence: both reach an overall pass rate of 81.60%, with the model excluding commodity prices exhibiting notably high convergence for A_t (93.72%) and Σ_t (88.17%).

Table 5.2: Geweke's Convergence Diagnostic Results

Model	B_t	A_t	Σ_t	Total
Baseline Model	73.59%	82.60%	78.44%	76.84%
Model Excluding Exchange Rate	80.35%	85.83%	80.94%	81.60%
Model Excluding Commodity Prices	72.70%	93.72%	88.17%	81.60%

Note: The table presents the proportion of parameters in each model group (B_t, A_t, Σ_t) for which Geweke's convergence diagnostic indicates no significant difference between the early and late segments of the Markov chains. A parameter is considered to have passed the Geweke test if its Z-score lies within the 95% confidence interval of a standard normal distribution, i.e., between -1.96 and $+1.96$. Higher proportions indicate greater evidence of convergence to the stationary distribution. The "Total" column reflects the overall share of parameters meeting the threshold across all groups. Note that this is not a simple average of the group-level proportions, as each group contains a different number of parameters. In the baseline model, B_t comprises 9,000 parameters, A_t 3,000, and Σ_t 7,500. In the alternative specifications, the corresponding group sizes are 6,000, 1,800, and 4,800 parameters, respectively.
Source: Own presentation of data collected from Banco Central do Brasil (2025a), Banco Central do Brasil (2025c), FRED (2025a), FRED (2025c), FRED (2025d), FRED (2025e), and World Bank Group (2025), compiled as indicated in Table 4.1 and processed in accordance with the methodology in Section 5.

Although these results do not indicate perfect convergence, they provide reasonably strong evidence that the Markov chains for most parameters have stabilized around the posterior distribution. This implies, that the Geweke results suggest that the sampling process was broadly successful. The few areas of underperformance, particularly among the B_t parameters, should be kept in mind when interpreting results, but they are not severe enough to compromise the validity of the inferences drawn from the posterior distributions.

The diagnostic results confirm that the baseline and alternative models converge appropriately and exhibit sufficient sampling efficiency, suggesting that the estimated parameters are robust and the model outputs reliable. With these diagnostics in place, the analysis now turns to the core empirical objective of the thesis: evaluating the dynamic effects of monetary policy shocks through IRFs.

6. Impulse Response Analysis

This section conducts an impulse response analysis within the TVP-SVAR-SV framework to evaluate the time-varying effects of monetary policy shocks on key macroeconomic variables in Brazil. The primary objective is to assess how these effects evolve over time and to what extent they depend on various transmission channels - specifically, the exchange rate and global commodity prices. These channels are investigated by comparing IRFs across the baseline model and the two alternative model specifications that systematically exclude each channel.

The section begins by introducing the concept of IRFs and their role in capturing dynamic interactions between variables in the time-varying setting of the TVP-SVAR-SV model. Structural shocks are applied to the monetary policy rate variable and the resulting dynamic responses of inflation and the output gap are examined. The estimated IRFs are then compared across the three models to isolate how the exclusion of the exchange rate or commodity prices affects the transmission of monetary policy.

IRFs illustrate the impact of a one-unit shock in one variable on the other variables within a vector model. In TVP-SVAR-SV models, the parameter estimates are available in the form of posterior distributions at each point in time. Since the IRFs depend on these parameter estimates, there exists a distinct IRF for each parameter in the posterior distribution at every time point. For the baseline model estimated in this thesis, consisting of 5 variables, 5,000 posterior draws per parameter, and 300 time points (equivalent to 25 years of monthly data), this results in a total of 37,500,000 distinct IRFs. This figure arises from 25 unique impulse-response combinations, each with 5,000 draws over 300 time points:

$$25 \times 5,000 \times 300 = 37,500,000 \tag{6.1}$$

Thus, even a single impulse-response pair yields 1,500,000 distinct IRFs, highlighting the complexity of interpreting time-varying responses without appropriate summarization. Additionally, each of the alternative model specifications, namely the model excluding the exchange rate variable and the model with no commodity prices, contain a total of 24,000,000 distinct IRFs:

$$16 \times 5,000 \times 300 = 24,000,000 \tag{6.2}$$

To simplify the presentation of these time-varying IRFs, the 50% percentile of the IRF distribution for an impulse-response pair at each time point is typically used to represent the point estimate (Nakajima, 2011, pp. 131). In addition to reporting the point estimates, this thesis also reports the credible intervals[6] for each

[6] In Bayesian statistics, credible intervals replace the traditional confidence intervals used in frequentist approaches. These intervals are interpreted similarly to confidence intervals (Nakajima, 2011, p. 119).

point estimate. Specifically, the 95% and 68% credible intervals, corresponding to the 2.5%, 16%, 84%, and 97.5% percentiles of the distribution of IRF estimates are reported, along with the 50% percentile point estimate. Furthermore, the thesis follows the methodology outlined in Mohanty & John (2015), reporting both time-invariant IRFs, calculated as the average response across time, and accumulated IRFs over a fixed horizon. The accumulated responses are illustrated as time series to highlight potential time-dependent variations in the IRFs. For an overview of the reported IRF estimates for all three model specifications, please refer to Appendix D.

In this thesis, the `bvarsv` package has been used to estimate the time-varying IRFs and the package offers three distinct methods for specifying IRF estimation. In alignment with Primiceri (2005), this thesis employs the third scenario in the package. In this scenario, the diagonal elements of the error term's variance-covariance matrix, Σ_t, are set to their time averages, reflecting the overall volatility of the variables. Meanwhile, the off-diagonal elements remain time-dependent, and thus captures the contemporaneous correlations between variables at each time point. This approach uses a dynamic representation of the transmission of shocks, thereby allowing for a more nuanced modelling of both the average volatility across variables and the changing interdependencies over time (Krüger, 2015, pp. 3-4 & Krüger, 2022, pp. 8-9). Once the IRFs have been estimated, the resulting responses are denormalized using the inverse of the standard scaler originally applied during preprocessing. This step ensures that the responses are expressed in their original units, preserving the interpretability of the variables involved.

The remainder of the section presents both time-invariant and accumulated time-varying IRFs for the three model specifications. Time-invariant responses are reported over a 60-month horizon to capture the full dynamic, including the initial impact, peak, and return to the long-term path. Meanwhile, accumulated time-varying IRFs are reported over an 18-month horizon, allowing sufficient time for shocks to fully transmit through the model. This is particularly important for monetary policy shocks, which, according to Zlobins (2025, pp. 28–30), typically reach their peak impact with a delay of around 12 to 18 months. This timing is further supported by the time-invariant IRF estimates from this thesis: as shown in Figures 6.2, 6.4, and 6.6, the effect of a monetary policy rate shock on inflation peaks after approximately 18 months. Thus, an 18-month window is considered appropriate to capture both the build-up and the peak of the response.

First, selected IRFs are presented for the baseline model. These are then compared to the corresponding IRFs from the two alternative models. This comparison allows for an assessment of how the exclusion of either the exchange rate or global commodity prices alters the estimated effects of monetary shocks on inflation and output gap. In doing so, the analysis highlights on the role of these external channels in shaping the dynamic trade-offs of monetary policy in Brazil.

6.1. Inflation, Output, and Policy Interactions in the Baseline Model

This section presents the impulse response analysis from the baseline TVP-SVAR-SV model, focusing on the dynamic interactions between inflation, the output gap, and the monetary policy rate. It begins by analysing the bidirectional responses between inflation and output, providing structural insights into the Phillips curve relationship. The section then turns to the core objective of the thesis, evaluating the effects of a monetary policy shock, by examining how an exogenous increase in the policy rate affects inflation and output over time. Together, these results illustrate the inflation-output trade-off embedded in Brazil's monetary policy regime. Moreover, they lay the empirical foundation for examining the effects of the exchange rate and commodity price channels in the remaining part of the section as well as for examining the policy trade offs in the form of the sacrifice ratio in Section 7.

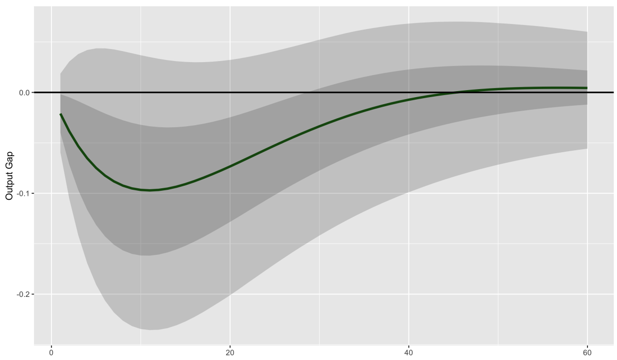
Figure 6.1 presents the impulse response results for two key relationships in the baseline TVP-SVAR-SV model: the effect of a positive inflation rate shock on the output gap, and the effect of a positive output gap shock on inflation. The left panel displays the time-invariant IRFs over a 60-month horizon, summarizing average dynamic responses across the full sample. The right panel shows accumulated time-varying IRFs over an 18-month horizon, capturing the evolution of cumulative effects from January 2000 to December 2024.

As shown in Figure 6.1a, a positive inflation shock leads to a statistically significant decline in the output gap at the 68% level. Initially, the response increases in magnitude, peaking after 11 months, and then gradually weakens before becoming statistically insignificant after 28 months. The time-varying accumulated IRF in Figure 6.1b confirms a consistently negative response at the 68% level throughout the sample, except for a brief period around early 2020. The magnitude of the response varies somewhat, appearing weaker from 2008–2010 and again after 2019, though these fluctuations are relatively modest. Figure 6.1c shows that a positive output gap shock increases inflation. The effect is significant at the 68% level, peaks after 11 months, with a maximum effect around 0.14%, and gradually declines, becoming insignificant after 30 months. The accumulated time-varying response remains significant at the 68% level over most of the sample, with a brief episode of 95% significance in early 2020 as seen in Figure 6.1d. The effect on inflation accumulates to approximately a 2% increase, but fluctuates slightly in the magnitude throughout the sample period.

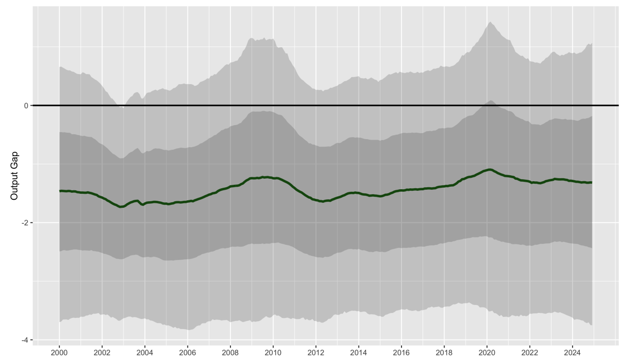
These findings align with the theoretical expectations of the Phillips curve: a positive inflation shock reduces real activity, likely due to a reduction in demand from higher prices, resulting in a negative output gap. Conversely, a positive output gap increases economic activity and generates upward pressure on prices, raising inflation (Gottfries, 2013, pp. 209–229 & pp. 235–250). Notably, the TVP-SVAR-SV framework captures these directional causal relationships more effectively than a simple correlation analysis. While Figure 4.4 only indicates a negative correlation, the structural model distinguishes between endogenous responses and exogenous shocks, showing that inflation-output dynamics depend on the source of the disturbance.

Figure 6.1: Trade-Off Between Inflation Rate and Output Gap in the Baseline Model

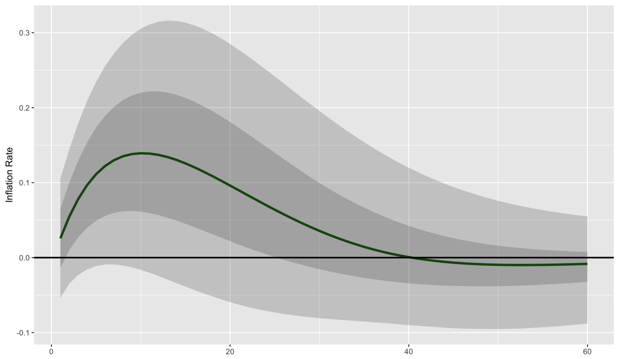
(a) Time-Invariant IRF: $\varepsilon_\pi \uparrow \rightarrow \hat{y}$



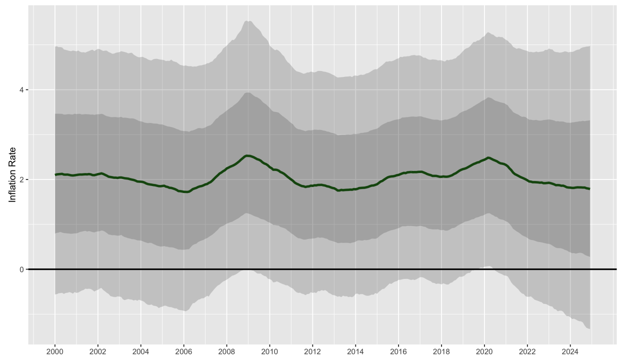
(b) Accumulated Time-Varying IRF: $\varepsilon_\pi \uparrow \rightarrow \hat{y}$



(c) Time-Invariant IRF: $\varepsilon_{\hat{y}} \uparrow \rightarrow \pi$



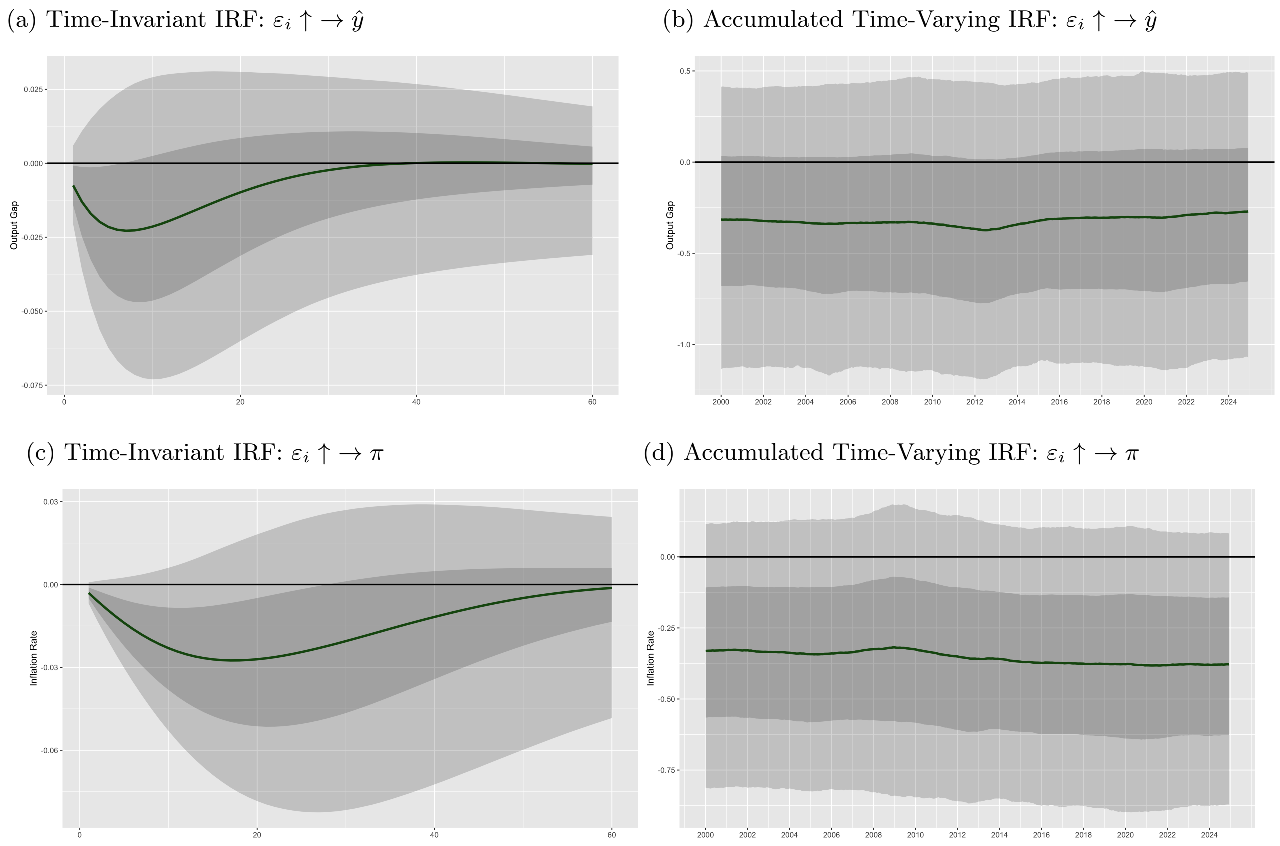
(d) Accumulated Time-Varying IRF: $\varepsilon_{\hat{y}} \uparrow \rightarrow \pi$



Note The figure presents the impulse response effects of an inflation rate shock (ε_π) on the output gap ($\hat{y}$) and an output gap shock ($\varepsilon_{\hat{y}}$) on the inflation rate (π) in the baseline model. For each variable, the left-hand panel displays the time-invariant average impulse response over a 60-month horizon, summarizing the IRF estimates across all time points. In contrast, the right-hand panel illustrates the accumulated 18-month impulse responses, highlighting the time-varying nature of the estimates. All panels include the 95% and 68% credible intervals.
Source: Own presentation of data collected from Banco Central do Brasil (2025a), Banco Central do Brasil (2025c), FRED (2025a), FRED (2025c), FRED (2025d), FRED (2025e), and World Bank Group (2025), compiled as indicated in Table 4.1 and processed in accordance with the methodology in Section 5.

Figure 6.2 presents the IRFs of a positive monetary policy rate shock on the output gap and inflation rate in the baseline model. As seen from Figure 6.2a, the initial effect of a monetary policy shock on the output gap is significantly negative in the first seven months within a 68% credible interval but not at a 95% credible interval. The response is increasingly negative and peaks approximately after six months before gradually fading. Figure 6.2b supports this pattern, showing a consistently negative accumulated response to the policy shock over the entire sample period, lingering around the 68% significance level. Notably, the magnitude of the effect intensifies from 2010 to 2012, suggesting that monetary policy shocks have had a stronger contractionary effect on the output gap in this period. In the remaining part of the period, the effect slightly decreases in magnitude. Moreover, this dynamic is consistent with the empirical relationship illustrated in Figure 4.2, which shows a slight negative correlation between the policy rate and the output gap in the descriptive statistical analysis.

Figure 6.2: A Shock to the Monetary Policy Rate in the Baseline Model



Note The figure presents the impulse response effects of a monetary policy rate shock (ε_i) on the output gap ($\hat{y}$) and inflation rate (π) response variables in the baseline model. For each variable, the left-hand panel displays the time-invariant average impulse response over a 60-month horizon, summarizing the IRF estimates across all time points. In contrast, the right-hand panel illustrates the accumulated 18-month impulse responses, highlighting the time-varying nature of the estimates. All panels include the 95% and 68% credible intervals.
Source: Own presentation of data collected from Banco Central do Brasil (2025a), Banco Central do Brasil (2025c), FRED (2025a), FRED (2025c), FRED (2025d), FRED (2025e), and World Bank Group (2025), compiled as indicated in Table 4.1 and processed in accordance with the methodology in Section 5.

These findings align with conventional macroeconomic theory, which states that an increase in the nominal interest rate, often implemented by the central bank to counter inflationary pressures, raises the cost of borrowing for households and firms. This, in turn, reduces consumption and investment, leading to a contraction in aggregate demand. With prices being sticky in the short run, this demand-side reduction does not immediately translate into lower inflation but instead results in a decline in real output. The gap between actual output and potential output thus widens, creating or deepening a negative output gap (Kriesler & Lavoie, 2007, Melmies, 2010). In the context of the estimated TVP-SVAR-SV model, the negative response of the output gap to a monetary policy shock reflects this contractionary channel. The increased magnitude in responses observed in the 2010-2012 period may further suggest that economic conditions have made the output gap more sensitive to interest rate changes during that time - potentially due to structural shifts in e.g., inflation expectations, fiscal support, or financial market integration.

In Figures 6.2c and 6.2d, the impulse response of the inflation rate to a positive monetary policy rate shock is presented. As shown in Figure 6.2c, the immediate response is significantly negative at the 68% credible level, reaching its peak magnitude after 16 months. Thereafter, the effect gradually diminishes and becomes statistically insignificant beyond 26 months. The accumulated time-varying IRFs in Figure 6.2d further support this finding: the inflation rate shows a consistently negative response to a monetary policy shock throughout the full sample period from 2000 to 2024 at the 68% significance level. Notably, the magnitude of the negative inflation response decreases from 2006 to 2009, before entering a slow trajectory towards increased responses for the remaining period. This suggests a structural change in the transmission mechanism of monetary policy, whereby interest rate increases have a more pronounced disinflationary effect in the later part of the sample.

From a theoretical standpoint, the observed disinflationary response aligns with standard macroeconomic theory: higher interest rates reduce aggregate demand by reducing consumption and investment, leading to downward pressure on prices (Kriesler & Lavoie, 2007). Therefore, the negative IRFs estimated here provide empirical support for the effectiveness of monetary policy in influencing inflation dynamics.

The results presented in Figure 6.2 show empirical support to the Phillips curve relationship, as they demonstrate that a contractionary monetary policy shock, here in the form of an increase in the policy interest rate, leads to a decline in both the output gap and inflation, although with different dynamics and timings. The negative response of output and inflation to the same shock suggests an inverse relationship between these two macroeconomic variables in the short run, consistent with the trade-off implied by the Phillips curve framework. Moreover, the findings also illustrates the logic embedded in the Taylor Rule, which guides central banks in setting interest rates in response to deviations of inflation from its target and output from its potential. The impulse responses illustrate the practical implications of this trade-off: raising interest rates may help stabilize inflation, but at the cost of a temporary reduction in output. These dynamics underscore the dual mandate often faced by central banks, balancing price stability with economic activity, and highlight the importance of careful policy calibration when responding to macroeconomic fluctuations.

6.2. Effects of the Exchange Rate Channel

This section investigates the role of the exchange rate in Brazil's monetary transmission mechanism by comparing results from the baseline model to those from a specification where the exchange rate variable is excluded. This allows for examining the extent to which the exchange rate channel alters the strength and timing of monetary transmission. The analysis begins by examining how a monetary policy shock affects the exchange rate in the baseline model, followed by an assessment of how exchange rate shocks transmit to the output gap and inflation. It then contrasts the estimated responses of output and inflation to monetary policy shocks in the baseline model and the model without the exchange rate.

Figure 6.3 illustrates the role of the exchange rate channel in the baseline TVP-SVAR-SV model by examining three key relationships: i) the effect of a monetary policy rate shock on the exchange rate, ii) the effect of an exchange rate shock on the output gap, and iii) the effect of an exchange rate shock on inflation.

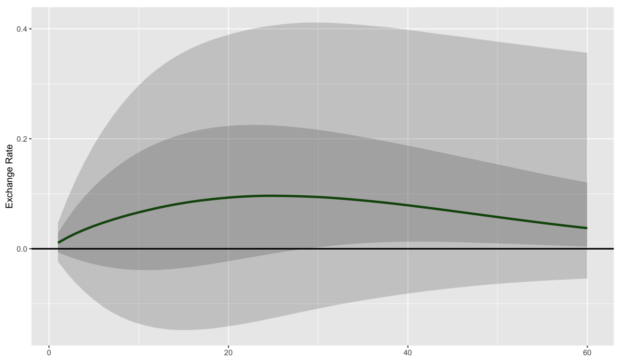
As shown in Figure 6.3a, the time-invariant average impulse response of the exchange rate following a monetary policy rate shock is generally small and statistically insignificant. Only after roughly 30 months does the response become significantly positive at the 68% credible interval. Accordingly, the accumulated 18-month IRFs in Figure 6.3b remain insignificant across the entire sample. This suggests that, contrary to standard open-economy macroeconomic theory, a positive interest rate shock does not consistently lead to an appreciation of the BRL (Gottfries, 2013, p. 379 & p. 388). Instead, the BRL tends to depreciate modestly and with a notable delay. This counter-intuitive finding may reflect Brazil's exposure to external financial conditions, or elevated risk premiums.

Turning to the effects of an exchange rate shock on the output gap, Figure 6.3c shows a generally negative pattern, though statistical significance is limited to the 68% level and occurs with a substantial delay, between 18 and 44 months after the shock. The accumulated time-varying IRFs in Figure 6.3d remain insignificant throughout the period. While a depreciation might be expected to boost net exports and output by improving external competitiveness, the results here suggest the opposite - likely because unexpected depreciations in Brazil are often associated with heightened uncertainty or external financial stress, as emerging market uncertainty can lead to a larger decrease in consumption, investment, and GDP compared to advanced countries (Chatterjee, 2024). In such cases, exchange rate shocks may undermine domestic demand through weaker investment and consumption, offsetting potential trade gains.

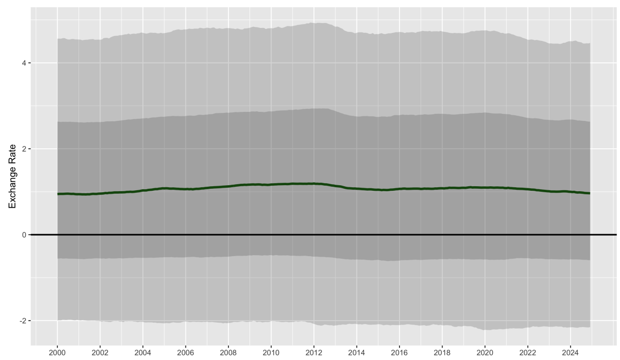
Figure 6.3e shows a clearer pattern: a depreciation of the BRL leads to a significant increase in inflation, with statistical significance at the 95% credible interval. The inflationary effect peaks after 12 months and then gradually fades. The accumulated 18-month IRFs in Figure 6.3f confirm this effect across most of the sample, with only a temporary decline in magnitude observed between 2005 and 2009. This result is consistent with the expectation that currency depreciation raises import prices and fuels inflationary pressure, particularly in emerging markets with high import dependence and weaker inflation anchoring.

Figure 6.3: Impulse Responses for the Exchange Rate Channel in the Baseline Model

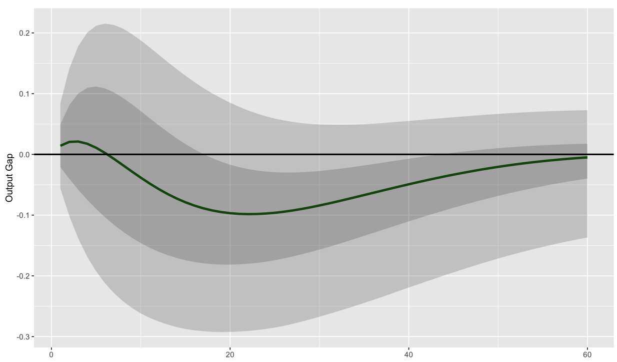
(a) Time-Invariant IRF: $\varepsilon_i \uparrow \rightarrow ex$



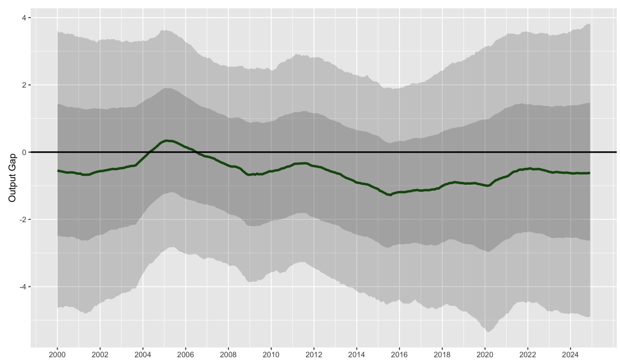
(b) Accumulated Time-Varying IRF: $\varepsilon_i \uparrow \rightarrow ex$



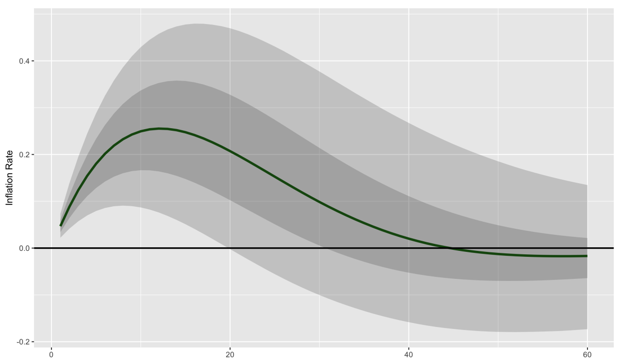
(c) Time-Invariant IRF: $\varepsilon_{ex} \uparrow \rightarrow \hat{y}$



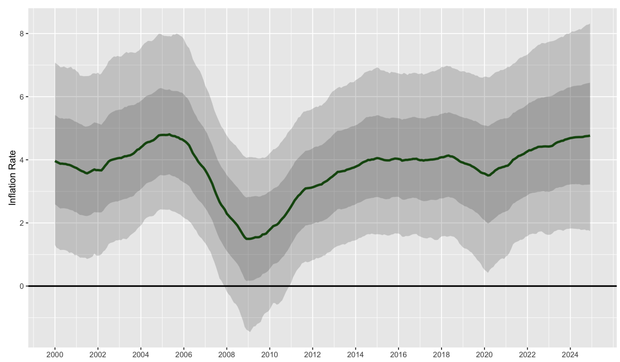
(d) Accumulated Time-Varying IRF: $\varepsilon_{ex} \uparrow \rightarrow \hat{y}$



(e) Time-Invariant IRF: $\varepsilon_{ex} \uparrow \rightarrow \pi$



(f) Accumulated Time-Varying IRF: $\varepsilon_{ex} \uparrow \rightarrow \pi$



Note The figure presents the impulse response effects of a monetary policy rate shock (ε_i) on the exchange rate (ex) as well an exchange rate shock (ε_{ex}) on the output gap ($\hat{y}$) and inflation rate (π) response variables in the baseline model. For each variable, the left-hand panel displays the time-invariant average impulse response over a 60-month horizon, summarizing the IRF estimates across all time points. In contrast, the right-hand panel illustrates the accumulated 18-month impulse responses, highlighting the time-varying nature of the estimates. All panels include the 95% and 68% credible intervals.
Source: Own presentation of data collected from Banco Central do Brasil (2025a), Banco Central do Brasil (2025c), FRED (2025a), FRED (2025c), FRED (2025d), FRED (2025e), and World Bank Group (2025), compiled as indicated in Table 4.1 and processed in accordance with the methodology in Section 5.

Taken together, the results suggest that the exchange rate channel in Brazil has an asymmetric role in the monetary transmission mechanism. It does not appear to amplify monetary tightening through currency appreciation, but it does transmit downside risks to output gap and upward pressure to inflation in the presence of currency depreciation. These dynamics are particularly relevant in a context where depreciations may signal economic instability rather than improved competitiveness. This characterization has direct implications for the responses involved in monetary policy rate shock. If the exchange rate channel primarily amplifies inflationary pressure and suppresses output in response to monetary tightening, then its presence may worsen the short-run cost of disinflation.

In the remaining part of this section, the analysis turns to the model without the exchange rate variable. By comparing the impulse responses across the two specifications, it is possible to assess whether the exclusion of the exchange rate alters the observed effects of a monetary policy rate shock on the output gap and inflation rate.

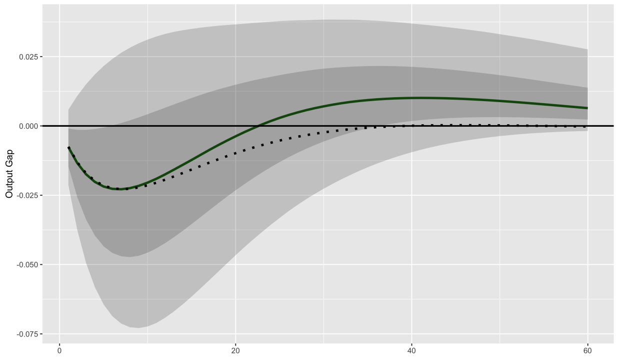
As seen in Figures 6.4a and 6.4b, the response of the output gap to a monetary policy rate shock is smaller in magnitude when the exchange rate channel is excluded compared to the baseline model. This suggests that the exchange rate amplifies the contractionary effects of monetary tightening on output. This finding aligns with the results in Figure 6.3, which show that a monetary policy shock tends to depreciate the BRL, and that a depreciation subsequently reduces the output gap. Excluding the exchange rate thus removes this transmission channel, resulting in a milder output contraction following an interest rate shock.

On the other hand, Figures 6.4c and 6.4d show that the response of inflation to a monetary policy rate shock is larger in magnitude when the exchange rate channel is excluded - implying a stronger disinflationary effect. This suggests that the exchange rate dampens the effectiveness of monetary tightening on inflation in the baseline model. In other words, when the exchange rate is allowed to adjust, part of the policy shock may be offset by exchange rate depreciation, which raises imported inflation and reduces the net disinflationary effect. By contrast, removing the exchange rate from the transmission mechanism eliminates this offsetting force, resulting in a more pronounced decline in inflation following a policy rate increase. This interpretation is supported by the results in Figure 6.3, which show that a depreciation of the BRL increases inflation. Thus, excluding the exchange rate allows monetary policy shocks to reduce inflation more effectively within the TVP-SVAR-SV framework.

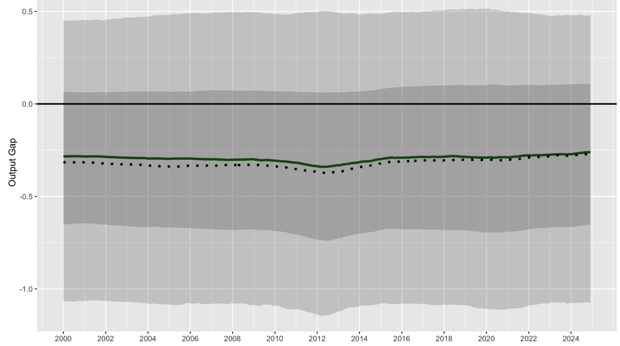
These findings suggest that the exchange rate channel can be a source of asymmetries in Brazil's monetary transmission. Contrary to standard theory, monetary tightening leads to a delayed depreciation of the BRL. This depreciation amplifies inflation and slightly weakens output. Excluding the exchange rate from the model leads to stronger disinflation and a milder output response, indicating that the exchange rate acts more as a source of friction than a shock absorber in Brazil's recent macroeconomic environment. These implications are further discussed in Section 7.

Figure 6.4: A Shock to the Monetary Policy Rate in the Model Excluding Exchange Rate

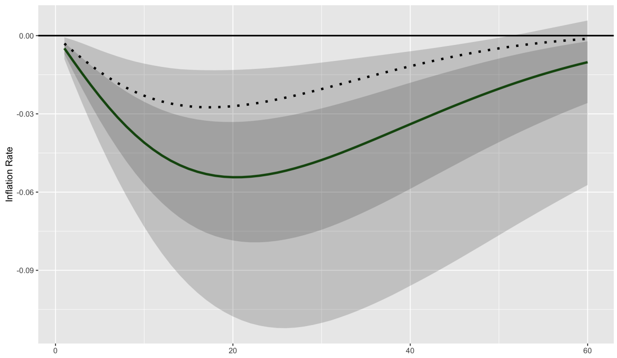
(a) Time-Invariant IRF: $\varepsilon_i \uparrow \rightarrow \hat{y}$



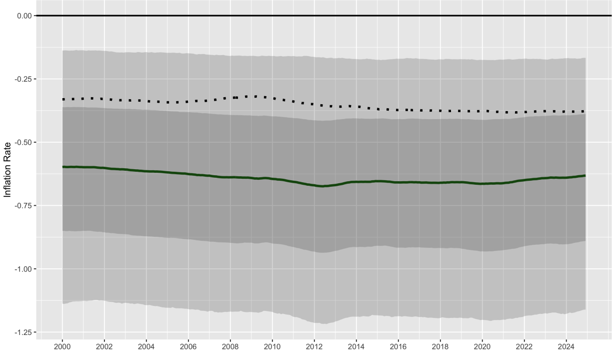
(b) Accumulated Time-Varying IRF: $\varepsilon_i \uparrow \rightarrow \hat{y}$



(c) Time-Invariant IRF: $\varepsilon_i \uparrow \rightarrow \pi$



(d) Accumulated Time-Varying IRF: $\varepsilon_i \uparrow \rightarrow \pi$



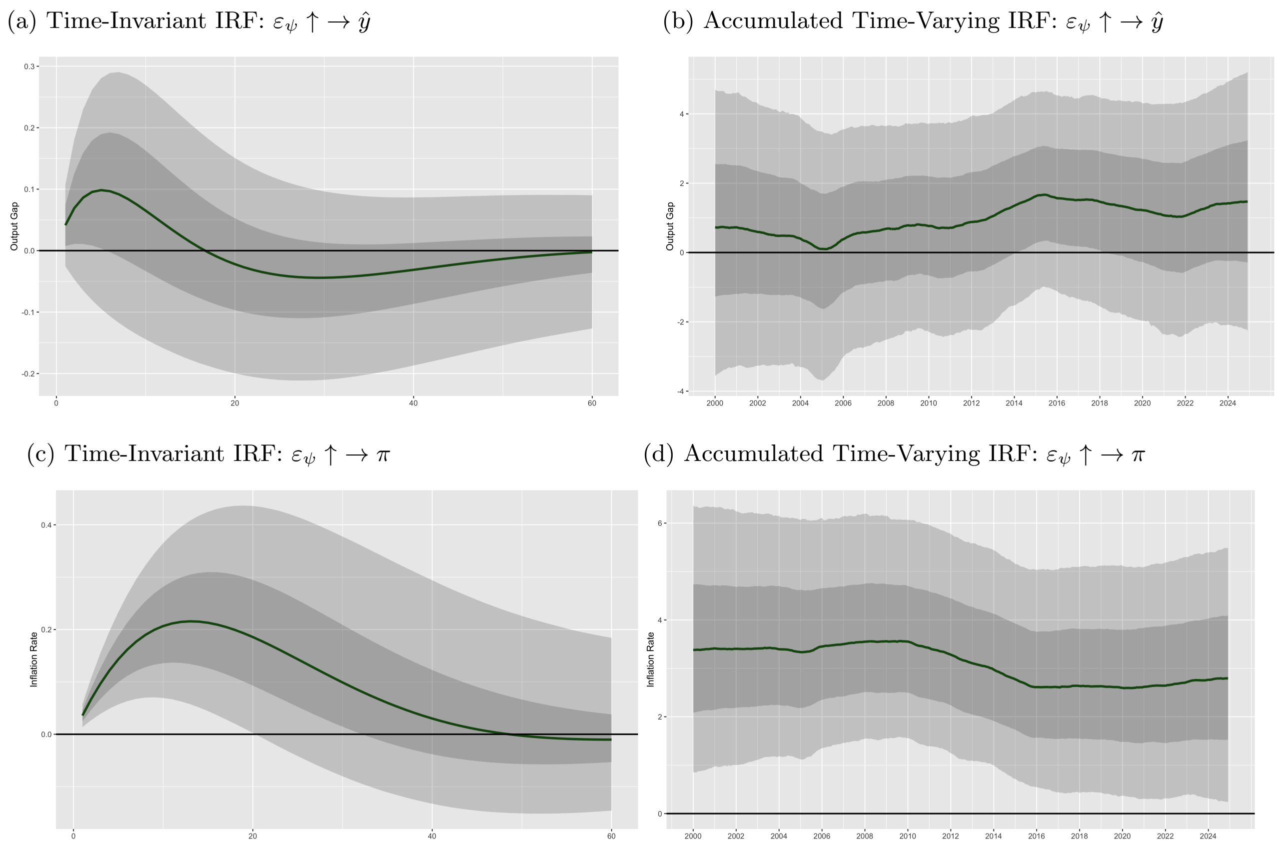
Note The figure presents the impulse response effects of a monetary policy rate shock (ε_i) on the output gap ($\hat{y}$) and inflation rate (π) response variables in the model with no exchange rate. For each variable, the left-hand panel displays the time-invariant average impulse response over a 60-month horizon, summarizing the IRF estimates across all time points. In contrast, the right-hand panel illustrates the accumulated 18-month impulse responses, highlighting the time-varying nature of the estimates. All panels include the 95% and 68% credible intervals as well as a dotted line for the corresponding impulse-response estimate in the baseline model.
Source: Own presentation of data collected from Banco Central do Brasil (2025a), Banco Central do Brasil (2025c), FRED (2025a), FRED (2025c), FRED (2025d), FRED (2025e), and World Bank Group (2025), compiled as indicated in Table 4.1 and processed in accordance with the methodology in Section 5.

6.3. Effects of the Commodity Price Channel

This section examines the influence of commodity prices on Brazil's monetary transmission mechanism. Following the same structure as in the previous section, the analysis first explores the role of commodity prices in the baseline model and then compares impulse responses to a monetary policy shock with those from a model that excludes the commodity price variable. This allows for assessing how the commodity price channel shapes the output–inflation trade-off.

The effect of a commodity price shock on the output gap is initially positive and statistically significant at the 68% level for the first four months, as seen in Figure 6.5a, before becoming insignificant. The accumulated 18-month response in Figure 6.5b confirms this pattern: the output gap response is generally positive, with significance at the 68% level only between 2014 and 2018. This result aligns with Brazil's role as a major commodity exporter: higher global commodity prices tend to boost export revenues and aggregate income, thereby supporting economic activity.

Figure 6.5: Impulse Responses for the Commodity Prices Channel in the Baseline Model



(a) Time-Invariant IRF: $\varepsilon_\psi \uparrow \rightarrow \hat{y}$

(b) Accumulated Time-Varying IRF: $\varepsilon_\psi \uparrow \rightarrow \hat{y}$

(c) Time-Invariant IRF: $\varepsilon_\psi \uparrow \rightarrow \pi$

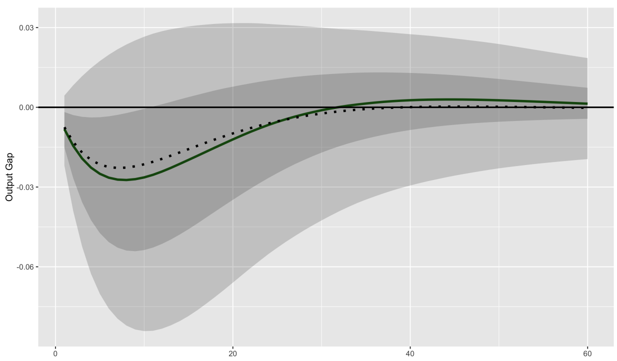
(d) Accumulated Time-Varying IRF: $\varepsilon_\psi \uparrow \rightarrow \pi$

Note The figure presents the impulse response effects of a commodity price shock (ε_ψ) on the output gap ($\hat{y}$) and inflation rate (π) response variables in the baseline model. For each variable, the left-hand panel displays the time-invariant average impulse response over a 60-month horizon, summarizing the IRF estimates across all time points. In contrast, the right-hand panel illustrates the accumulated 18-month impulse responses, highlighting the time-varying nature of the estimates. All panels include the 95% and 68% credible intervals.
Source: Own presentation of data collected from Banco Central do Brasil (2025a), Banco Central do Brasil (2025c), FRED (2025a), FRED (2025c), FRED (2025d), FRED (2025e), and World Bank Group (2025), compiled as indicated in Table 4.1 and processed in accordance with the methodology in Section 5.

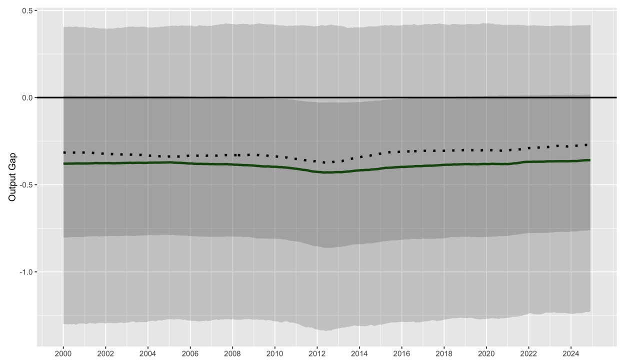
Turning to inflation, Figures 6.5c and 6.5d indicate that a positive commodity price shock leads to a statistically significant increase in inflation with a significance at the 95% credible level. The inflationary response peaks after 14 months before gradually declining as seen in the average time-invariant IRF. The time-varying accumulated IRF shows that the inflationary impact was stronger in the first half of the sample, before declining between 2010 and 2016, and then remained relatively stable at the lower level through the remainder of the period. This positive relationship between commodity prices and inflation aligns with theoretical expectations. As Brazil is a large importer of commodities as petroleum, gas, rice and so on (The Obsevatory of Economic Complexity, 2025), rising global commodity prices can increase input costs and producer prices, which are eventually passed through to consumers. Additionally, higher global food and energy prices directly raise the headline inflation rate.

Figure 6.6: A Shock to the Monetary Policy Rate in the Model Excluding Commodity Prices

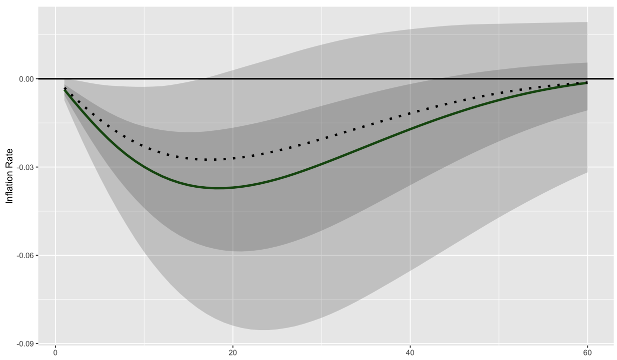
(a) Time-Invariant IRF: $\varepsilon_i \uparrow \rightarrow \hat{y}$



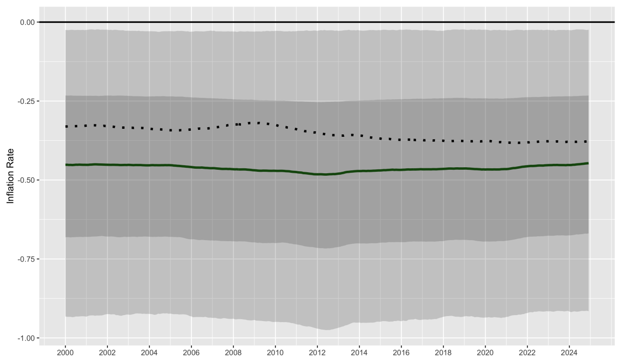
(b) Accumulated Time-Varying IRF: $\varepsilon_i \uparrow \rightarrow \hat{y}$



(c) Time-Invariant IRF: $\varepsilon_i \uparrow \rightarrow \pi$



(d) Accumulated Time-Varying IRF: $\varepsilon_i \uparrow \rightarrow \pi$



Note The figure presents the impulse response effects of a monetary policy rate shock (ε_i) on the output gap ($\hat{y}$) and inflation rate (π) response variables in the model with no commodity prices. For each variable, the left-hand panel displays the time-invariant average impulse response over a 60-month horizon, summarizing the IRF estimates across all time points. In contrast, the right-hand panel illustrates the accumulated 18-month impulse responses, highlighting the time-varying nature of the estimates. All panels include the 95% and 68% credible intervals as well as a dotted line for the corresponding impulse-response estimate in the baseline model.
Source: Own presentation of data collected from Banco Central do Brasil (2025a), Banco Central do Brasil (2025c), FRED (2025a), FRED (2025c), FRED (2025d), FRED (2025e), and World Bank Group (2025), compiled as indicated in Table 4.1 and processed in accordance with the methodology in Section 5.

The positive responses in output gap and inflation following a shock to commodity prices indicate that the commodity price channel plays a meaningful role in Brazil's monetary transmission mechanism, particularly through its influence on inflation. This implies that fluctuations in commodity prices significantly affect inflation and, to a lesser extent, the output gap. This is consistent with Brazil's economic structure, where global commodity dynamics feed into domestic prices and, at times, stimulate real activity via the export sector.

Importantly, the presence of this channel implies that external price shocks may complicate the task of monetary stabilization by amplifying inflationary pressures.

To assess how this mechanism influences the overall transmission of monetary policy, the analysis now turns to the model in which commodity prices are excluded. By comparing impulse responses of a monetary policy rate shock across the two specifications, it becomes possible to evaluate the extent to which the commodity price channel shapes the output gap and inflation responses in Brazil. As seen in Figure 6.6, the responses of both the output gap and inflation to a monetary policy rate shock are larger in magnitude in the model excluding commodity prices. This suggests that the commodity price channel dampens the contractionary effect of monetary tightening on output and weakens its disinflationary impact.

6.4. Partial Conclusion

This section has examined the dynamic responses of inflation and output gap to monetary policy shocks through a TVP-SVAR-SV framework, with a particular focus on the roles of the exchange rate and commodity price channels. The analysis shows that monetary tightening in Brazil produces contractionary effects on the output gap and results in downward pressure on inflation, broadly consistent with macroeconomic theory. These effects vary in strength across time, reflecting evolving structural conditions and potentially changing monetary transmission mechanisms.

The inclusion or exclusion of external channels plays a significant role in shaping these dynamics. In the case of the exchange rate, results indicate that monetary tightening does not lead to currency appreciation, as theory would predict. Instead, the BRL tends to depreciate modestly after a delay, which weakens output and adds to inflationary pressure. When the exchange rate channel is excluded from the model, the output gap response becomes milder and the disinflationary effect of monetary policy increases, suggesting that the exchange rate acts as a friction in the Brazilian context, rather than as a stabilizing mechanism.

By contrast, the commodity price channel appears to be more closely aligned with theoretical expectations in terms of directional impact: commodity price increases raise both output and inflation. Moreover, when the commodity price variable is excluded from the model, the estimated responses of inflation and output gap to a monetary shock are larger, suggesting that this channel reduces the contractionary effect of monetary tightening on output as well as decreases its disinflationary impact.

Overall, the impulse response analysis highlights that while Brazil's monetary policy has the expected directional effects, the strength and timing of those effects depend critically on the external channels considered. These findings provide a valuable foundation for the policy trade-off analysis carried out in Section 7, where the output–inflation trade-off will be examined in greater detail across the different model specifications using the principles of the sacrifice ratio.

7. Measuring the Policy Trade-Off

This section analyses the policy trade-off of monetary policy. Specifically, how much output must be sacrificed to reduce inflation in Brazil. The sacrifice ratio is calculated at each point in time to assess how this trade-off evolved from January 2000 to December 2024, offering insight into the changing effectiveness of monetary policy over time. The effectiveness is calculated from the baseline model and then compared against the alternative models, one excluding the exchange rate variable and one without the commodity price variable.

The sacrifice ratio measures the output cost of reducing inflation. Specifically, it specifies how much output must be lost to lower inflation by one percentage point. This metric is useful for evaluating the effectiveness of monetary policy; a lower ratio indicates that disinflation can be achieved at a smaller economic cost, thereby suggesting a higher policy effectiveness.

In this thesis, the sacrifice ratio is calculated using IRFs from the TVP-SVAR-SV model over an 18-month horizon. Specifically, the sacrifice ratio at time t is defined as the ratio of the cumulative output gap response to the level change in inflation, both following a one-standard-deviation monetary policy shock:

$$\mathrm{SR}_t = \frac{\sum_{j=0}^{\tau} \frac{\partial \hat{y}_{t+j}}{\partial \varepsilon_t^i}}{\frac{\partial \pi_{t+\tau}}{\partial \varepsilon_t^i}} = \frac{\text{Cumulative Output Gap Response}_{t,\tau}}{\text{Inflation Reduction}_{t,\tau}} \tag{7.1}$$

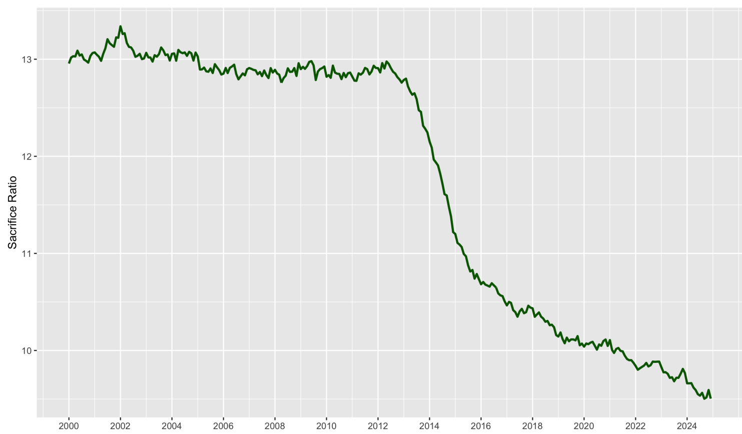
Here, SR_t denotes the sacrifice ratio at time t, $\hat{y}$ is the output gap, π is the inflation rate, and ε_t^i represents a structural shock to the monetary policy rate. The numerator captures the total output loss over a horizon $\tau = 18$ months, while the denominator reflects the corresponding change in the price level at the end of the horizon. This definition follows the methodology outlined in Cecchetti & Rich (2001, pp. 7–10). This approach yields a monthly, time-varying sacrifice ratio from January 2000 to December 2024, as illustrated in Figure 7.1. The metric allows for analysing how the output cost of disinflation evolves over time.

As shown in Figure 7.1, Brazil's sacrifice ratio begins the sample period at approximately 13 and remains relatively stable at that level until around 2005, with only a temporary spike in 2002. From 2005 to 2012, a modest downward trend is observed. This is followed by a sharper decline between 2012 and 2016, where the ratio falls from roughly 13 to 10.7. From 2016 to 2024, the decline continues at a slower pace, ending near 9.5. This decline can be explained by looking at the 18-month accumulative response in the output gap and inflation following a positive monetary policy rate shock illustrated in Figures 6.2b and 6.2d. As seen in the figures, the response of the inflation rate to a monetary policy shock is slightly larger in magnitude after 2012. At the same time, the response of the output gap decreases slightly in magnitude. As a result, the monetary policy becomes slightly more effective in regards to its level effect on inflation and slightly less contractive on output, implying that the policy trade-off of a monetary policy rate shock is improved.

Interestingly, the global financial crisis and its immediate aftermath appear to have had little direct effect on the sacrifice ratio. However, a more noticeable drop occurs shortly afterward during a period marked by rising commodity prices, a depreciating exchange rate, a positive output gap, and only mild inflationary pressures. The subsequent period of stagflation in 2015–2017, characterized by falling output and commodity prices alongside rising inflation, also coincides with continued reductions in the sacrifice ratio, despite exchange rate volatility. In the post-2020 period, global shocks such as the COVID-19 pandemic and the ensuing inflation surge create non-standard conditions, including sharp demand fluctuations (World Bank, 2020) and large fiscal interventions (IMF, 2020), which affects the traditional policy transmission mechanisms.

The sustained decline in the sacrifice ratio after 2012 suggests that disinflation has become less costly in terms of output loss, implying a rising effectivenss of Brazil's monetary policy in the latter part of the sample. This shift could reflect improvements in macroeconomic governance, institutional credibility, and policy design, which collectively strengthened the central bank's ability to manage inflation expectations.

Figure 7.1: Sacrifice Ratio for Baseline Model, 2000M1-2024M12



Note: The figure displays the monthly evolution of the sacrifice ratio in the baseline TVP-SVAR-SV model from January 2000 to December 2024. The sacrifice ratio is calculated as the cumulative response of the output gap relative to the level response of inflation 18 months after a monetary policy rate shock. Higher values indicate a greater output cost for reducing inflation, while lower values reflect more efficient monetary policy transmission.
Source: Own presentation of data collected from Banco Central do Brasil (2025a), Banco Central do Brasil (2025c), FRED (2025a), FRED (2025c), FRED (2025d), FRED (2025e), and World Bank Group (2025), compiled as indicated in Table 4.1 and processed in accordance with the methodology in Section 5.

One key factor in this development may be the BCB's institutional evolution. The implementation of an inflation-targeting regime in 1999, along with reforms aimed at enhancing transparency and accountability, likely contributed to increased policy credibility. As argued by ECB (n.d.), credibility can anchor inflation expectations and reduce the need for large interest rate adjustments, thereby lowering the output cost of disinflation.

This interpretation is supported by findings in Tunali (2008), who examines how specific features of monetary policy frameworks influence the sacrifice ratio. Using cross-country data and a 2SLS estimation strategy, the study finds that while adopting inflation targeting per se does not significantly reduce disinflation costs, institutional characteristics, such as limits on policy discretion and prohibitions on central bank financing of fiscal deficits, are strongly associated with lower sacrifice ratios, especially among OECD countries. The relationship is even stronger when countries with weak institutional frameworks are excluded, suggesting that institutional quality is a key determinant of monetary policy effectiveness.

In addition to institutional design, effective communication and forecast transparency are central to enhancing monetary policy credibility. Chortareas et al. (2002) show that greater forecast transparency is associated with significantly lower sacrifice ratios across OECD economies. Specifically, they estimate that a one-point increase in transparency reduces the sacrifice ratio by 0.71, highlighting the importance of managing expectations in reducing the output cost of disinflation.

In the Brazilian context, these findings underscore the potential benefits of the post-1999 reforms. Under the inflation-targeting regime, the BCB introduced several transparency measures, including the publication of inflation targets, forward-looking guidance, and formal accountability requirements. Notably, the BCB is required to issue an open letter to the Minister of Finance if inflation breaches the official target band, thereby reinforcing the commitment to price stability and enhancing public trust in monetary policy (Banco Central do Brasil, n.d.-c). Although the sacrifice ratio cannot be computed prior to 2000 due to data limitations and the burn-in period for the TVP-SVAR-SV model, the downward trend observed over the sample period may reflect the gradual credibility gains associated with these institutional and procedural reforms.

However, transparency alone does not guarantee policy credibility. A comparison between Figure 7.1 and Figure 2.1, which presents the inflation target range alongside actual inflation outcomes, shows that episodes of rising sacrifice ratios often coincide with breaches of the inflation target band. This suggests that when inflation consistently deviates from target, transparency may be insufficient to maintain the public's confidence in the central bank's ability to deliver on its mandate. For instance, in 2002, inflation was well above the target range, and this coincided with a noticeable spike in the sacrifice ratio. A similar pattern can be observed in 2015, when another breach of the upper bound of the target was associated with a slowdown in the improvement of the sacrifice ratio. More recently, in 2021–2022, inflation again rose above the target range. During this period, the sacrifice ratio appears to have flattened out temporarily around 2020–2021 before resuming its downward trend thereafter.

These deviations indicate that while the BCB adopted transparency-enhancing reforms early on, their credibility likely took time to consolidate. The early years of the inflation-targeting regime followed a period of high inflation volatility, and the public may have initially remained cautious about BCB's ability to maintain price stability. Consequently, the sacrifice ratio declined only gradually during the early 2000s, potentially reflecting the time required to build policy credibility. As inflation targeting gained traction and became more stable, expectations may have become more firmly anchored, reducing the output cost of disinflation. When inflation targets are missed, especially repeatedly, the public may begin to question whether the central bank is either willing or able to act decisively, undermining the credibility of its commitments. If inflation expectations become less well-anchored, achieving disinflation requires stronger policy interventions, which raises the sacrifice ratio.

These observations reinforce the argument presented by Chortareas et al. (2002) and Tunali (2008): transparency must be matched by consistent performance to be effective. Inflation targeting frameworks can only stabilize expectations and improve monetary effectiveness when they are perceived as both credible and achievable. The steady improvement in Brazil's sacrifice ratio over the sample period likely reflects a maturing policy regime - one that increasingly succeeds in anchoring expectations and lowering the real costs of disinflation.

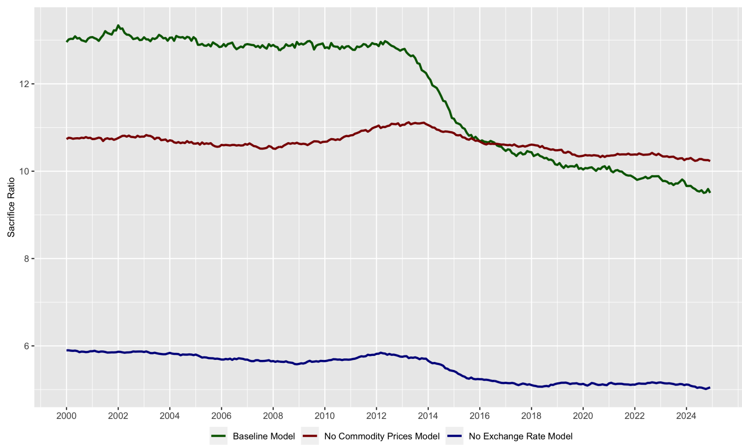
7.1. Examination of Exchange Rate and Commodity Price Channels

Having established the time-varying evolution of Brazil's sacrifice ratio in the baseline model, this section turns to a comparative analysis of how the exchange rate and global commodity prices channels shape the effectiveness of monetary policy over time. By comparing the sacrifice ratios generated by the baseline specification to those derived from models that exclude each channel in turn, the analysis seeks to isolate the role these mechanisms play in amplifying or dampening the trade-off between disinflation and output loss. This approach builds directly on the impulse response findings from Section 6, allowing for an assessment of how the presence or absence of these channels alters the macroeconomic cost of achieving lower inflation in Brazil.

Figure 7.2 presents the evolution of the sacrifice ratio across all three model specifications: the baseline model, the model excluding commodity prices, and the model excluding the exchange rate. The baseline model exhibits the most substantial improvement in monetary policy effectiveness, with the sacrifice ratio falling by approximately 3.5 points between 2000 and 2024. In contrast, the model without commodity prices shows a relatively flat sacrifice ratio in the early part of the sample, followed by a temporary deterioration between 2010 and 2012. A gradual improvement emerges thereafter, with the ratio ending around 0.5 points lower than at the start of the period. The model without the exchange rate variable shows a more moderate and consistent improvement, particularly from 2012 onward, resulting in a total reduction of approximately 1 point over the full period.

A comparison of the three series reveals that the model excluding commodity prices initially exhibits a lower sacrifice ratio than the baseline model. This can be attributed to the negative response in inflation following a monetary policy rate shock being larger in the model excluding the commodity prices as seen in Figure 6.6d by approximately 0.12 points. This more than offsets the more contractionary effect of about 0.06 point on the output gap in the model excluding commodity prices, resulting in an initially lower sacrifice ratio. However, from around 2016 onward, the baseline model outperforms the model without commodity prices, reflecting a more favourable output–inflation trade-off. This shift can be partly explained by two developments: i) the difference in inflation response between the two models narrows over time, and ii) the output contraction becomes more pronounced in the model excluding commodity prices. Comparing the IRFs in Figure 6.6d with the development of commodity prices shown in Figure 4.6c, it is evident that the decline in commodity prices and output becomes more pronounced after 2012. This coincides with a period where the sacrifice ratio initially increases slightly before declining again. This suggests that, prior to the decline in commodity prices, the inflation-output trade-off may have been more severe relative to the baseline model. However, the subsequent fall in commodity prices could have enhanced the effectiveness of monetary policy, as indicated by the comparison between the baseline model and the specification excluding commodity prices.

Figure 7.2: Sacrifice Ratio for All Model Specifications, 2000M1-2024M12



Note: The figure displays the monthly evolution of the sacrifice ratio from January 2000 to December 2024 across three TVP-SVAR-SV model specifications: the baseline model (green), the model excluding the exchange rate variable (blue), and the model excluding commodity prices (red). In each case, the sacrifice ratio is computed as the cumulative response of the output gap relative to the level response of inflation 18 months after a monetary policy rate shock. Comparing the trajectories allows for an assessment of how the exchange rate and commodity prices transmission channels alter the trade-off between disinflation and output loss.
Source: Own presentation of data collected from Banco Central do Brasil (2025a), Banco Central do Brasil (2025c), FRED (2025a), FRED (2025c), FRED (2025d), FRED (2025e), and World Bank Group (2025), compiled as indicated in Table 4.1 and processed in accordance with the methodology in Section 5.

In contrast, the model excluding the exchange rate channel consistently yields the lowest sacrifice ratio across the entire sample period. Specifically, this model is 4.5 to 7 points lower than the baseline, depending on the time period. This result aligns with the impulse responses shown in Figure 6.3, where the model without the exchange rate channel shows both a stronger impact of monetary policy on inflation and a milder impact on the output gap. Specifically, the inflation response strengthens from approximately –0.35% in the baseline to –0.65% in the model without the exchange rate, while the effect on output gap remains relatively muted. This consistent improvement helps explain the persistently lower sacrifice ratio.

The baseline model suggests that monetary tightening tends to depreciate the BRL, and such depreciation is associated with higher inflation and lower output. This introduces a feedback loop: interest rate hikes lead to currency depreciation, which in turn raises import prices and inflation - thereby offsetting the intended disinflationary effect and amplifying output losses. Excluding the exchange rate channel breaks this loop, resulting in more effective transmission of monetary policy and a lower sacrifice ratio. This counter-intuitive depreciation response, in the form of tightening leading to a weaker currency, can be explained by Brazil's exposure to capital flow volatility. In an emerging market context, higher interest rates may be interpreted not as a sign of policy credibility but as an indication of heightened fiscal or economic risk. This perception can trigger capital outflows, weakening the currency. A depreciated exchange rate, in turn, raises the cost of imported goods and may also increase the burden of external debt if a large share is denominated in foreign currency. These dynamics compound the inflationary and contractionary effects of exchange rate movements, helping to explain why excluding this channel results in more efficient monetary policy transmission.

Turning to the commodity price channel, the picture is more nuanced. The model excluding commodity prices yields a slightly lower sacrifice ratio in the early 2000s, but this advantage disappears after 2016, as the baseline model shows stronger improvements. This result is consistent with the impulse response analysis in Figure 6.5, which shows that positive commodity price shocks tend to increase both inflation and output. Over time, however, the inflationary response appears to decline, while the output response becomes stronger.

This can be explained by commodity prices playing a dual role in the Brazilian economy. As a major exporter of agricultural and raw materials, rising global prices boost Brazil's export revenues and output. At the same time, increases in food and energy prices raise domestic inflation through cost-push mechanisms. In the earlier part of the sample, this inflationary pressure may have dominated, meaning that excluding commodity prices yielded a more favourable output–inflation trade-off. However, after 2016, the improved output effect appears to outweigh the inflationary impact, leading to a better sacrifice ratio in the baseline model. Brazil's 2015–2017 stagflation episode is illustrative in this regard. During this period, falling commodity prices, declining output, and elevated inflation coexisted (ECB, 2016). Removing the commodity price channel in the model during such episodes may suppress important external influences on inflation and output, potentially biasing the results. Over the full sample, it appears that the baseline model's inclusion of commodity prices ultimately allows for a more accurate characterization of macroeconomic dynamics, particularly in the second half of the period.

7.2. Partial Conclusion

In this section, the policy trade-offs embedded in Brazil's monetary policy has been examined by analysing the time-varying sacrifice ratios. The results indicate a steady decline in the sacrifice ratio from 2000 to 2024, suggesting that disinflation became gradually less costly in terms of output loss. This improvement in monetary policy effectiveness is likely linked to the BCB's institutional strengthening - most notably, the adoption of an inflation-targeting regime and reforms aimed at enhancing transparency and credibility. Nevertheless, the analysis also reveals that credibility must be earned and maintained over time: periods of inflation target breaches coincide with slower declines or temporary increases in the sacrifice ratio, suggesting that transparency alone is insufficient if not supported by consistent policy performance.

The subsequent comparison of alternative model specifications, one excluding the exchange rate and another excluding commodity prices, highlights the distinct roles these external channels play in shaping the output–inflation trade-off. Excluding the exchange rate consistently yields a lower sacrifice ratio, indicating that exchange rate depreciation in response to monetary tightening can undermine disinflation efforts and amplify output losses. This asymmetry suggests that in Brazil's context, the exchange rate channel functions more as a friction than a stabilizer. The commodity price channel presents a more mixed picture: while excluding it initially improves the trade-off, this advantage fades over time, and the baseline model outperforms from 2016 onward. This shift reflects a growing contribution of commodity price shocks to output support rather than inflationary pressure in the later period.

Together, these findings demonstrate the value of a time-varying approach to evaluating monetary policy effectiveness and highlight the importance of considering external transmission channels in open economies like Brazil. They also underscore that improving monetary effectiveness is not solely a question of policy tools, but also of institutional design, credibility, and responsiveness to evolving macroeconomic conditions.

While the time-varying sacrifice ratio provides valuable insights into the evolving trade-offs of monetary policy in Brazil, these findings ultimately rest on the assumptions and structure of the underlying TVP-SVAR-SV model. To ensure that the conclusions drawn are robust and not a result of specific modelling choices, the following section critically evaluates the empirical validity of the model. This includes both robustness checks and a discussion of alternative identification strategies that could address potential limitations.

8. Validity of Estimated Models and Alternatives

This section evaluates the empirical validity of the TVP-SVAR-SV model used in the thesis. It is divided into two parts. The first part presents the results of robustness checks designed to assess the sensitivity of the main findings to key modelling assumptions. Specifically, it tests how changes in the variable ordering used for shock identification, and alternative measures of the exchange rate, affect the estimated impulse responses and policy trade-offs.

The second part critically examines the broader strengths and limitations of the TVP-SVAR-SV framework. It focuses in particular on the challenge of identifying exogenous monetary policy shocks in dynamic macroeconomic settings, where central banks act on expectations rather than current data. As part of this discussion, the section introduces alternative identification strategies, most notably, the narrative-based approach proposed by Romer & Romer (2004), and assesses their feasibility and relevance in the Brazilian context. While the time-varying structure of the TVP-SVAR-SV model mitigates some of the limitations inherent in traditional VAR approaches, issues of shock identification and endogeneity remain and warrant further discussion.

8.1. Robustness of Results

To ensure the validity and credibility of the empirical findings, two key robustness checks were conducted. These aimed to test the sensitivity of the results obtained in the initial model specifications to alternative modelling assumptions, particularly regarding variable ordering in the identification scheme and the specification of the exchange rate variable. A full presentation of the robustness results, including impulse response comparisons, is available in Appendix E.

The first robustness check reorders the variables in the contemporaneous impact matrix to examine how changes in assumed causal structure affect the IRFs. Specifically, inflation is assumed to be contemporaneously affected by the output gap rather than vice versa. This adjustment reflects an alternative economic rationale where domestic demand conditions have an immediate effect on price dynamics. Thus, the revised identification order is:

$$A_t^{\text{New}} \left(\begin{bmatrix} \psi_t \\ i_t \\ ex_t \\ \hat{y}_t \\ \pi_t \end{bmatrix} \right) = \begin{bmatrix} 1 & 0 & 0 & 0 & 0 \\ \alpha_{21,t} & 1 & 0 & 0 & 0 \\ \alpha_{31,t} & \alpha_{32,t} & 1 & 0 & 0 \\ \alpha_{41,t} & \alpha_{42,t} & \alpha_{43,t} & 1 & 0 \\ \alpha_{51,t} & \alpha_{52,t} & \alpha_{53,t} & \alpha_{54,t} & 1 \end{bmatrix} \tag{8.1}$$

Despite this fundamental change, the qualitative features of the IRFs remain largely intact. The responses of output and inflation to monetary policy shocks follows the same overall trajectory as in the original model specification, indicating that the identification of monetary policy shocks is not overly sensitive to the precise recursive ordering. Nevertheless, some minor variations in magnitude and timing are observed, particularly in the inflation responses, which suggests that although the TVP-SVAR-SV model is generally robust, it does contain a degree of sensitivity to identification assumptions.

The second robustness check replaces the bilateral BRL/USD exchange rate with the effective exchange rate, which measures the relative value of the BRL against a broader basket of major trading partners. This is a more comprehensive measure, potentially better capturing global monetary transmission channels. The empirical responses using the effective exchange rate are consistent with the findings of the original specifications. In particular, the output gap and inflation dynamics in response to monetary policy shocks preserve their general patterns. However, the level of the sacrifice ratios are generally increased for the baseline model and the model excluding the commodity prices. This supports the view that while the bilateral BRL/USD rate captures relevant dynamics, the broader external environment captured by the effective rate introduces a moderating influence that may better reflect Brazil's trade-weighted exposure to exchange rate dynamics, leading to a worsening of the policy trade-off.

Overall, the robustness checks confirm the stability of the core findings across reasonable alternative assumptions. Yet, this robustness is not absolute. The results exhibit some degree of sensitivity to changes in the identification strategy and the operationalisation of the exchange rate. Hence, while the robustness exercises reinforce the empirical credibility of the results obtained from the original specifications of TVP-SVAR-SV framework, they also highlight the need for cautious interpretation.

8.2. Strenghts and Limitations of Model Framework

The TVP-SVAR-SV model used in this thesis is designed to accommodate evolving macroeconomic relationships and volatility over time. This flexibility is particularly important in an economy like Brazil, where structural changes, regime shifts, and external shocks have frequently altered the economic environment. However, one persistent challenge is the identification of truly exogenous monetary policy shocks. Central banks respond to forecasts of future macroeconomic conditions, not merely to current or past data. This forward-looking behaviour introduces endogeneity that standard VAR identification techniques may fail to address adequately.

This critique is discussed in detail by Rudebusch (1998), who argues that traditional VAR models are fundamentally flawed for analysing monetary policy. Key limitations include: i) the assumption of constant policy behaviour across time, ii) the poor alignment between VAR-identified shocks and financial market-based surprises, and iii) contradictory impulse response patterns across specifications. These shortcomings motivate the move toward time-varying models like the one employed here. However, while the TVP-SVAR-SV framework addresses issues of parameter stability and evolving volatility, it still relies on a recursive identification strategy that may inadequately disentangle exogenous policy actions from endogenous responses to expected conditions.

A more direct response to this identification challenge is offered by Romer & Romer (2004), who propose a narrative-based approach to isolate exogenous monetary policy shocks. Their method relies on internal Federal Reserve documents to construct a series of intended policy rate changes around scheduled FOMC meetings. From this series, they exclude components correlated with the Fed's internal forecasts (Greenbook projections), interpreting the residuals as unexpected, exogenous shocks. The basis for this methodology is that the Greenbook projections represent the best available information to policymakers at the time of decision-making. By excluding components that correlate with these projections, Romer & Romer (2004) remove the part of the policy change which are based on expected economic conditions. As a result, this approach effectively filters out anticipated policy changes driven by evolving macroeconomic expectations, isolating only the unforecasted policy interventions.

Empirically, Romer & Romer (2004) find that this narrative approach yields stronger and more coherent effects of monetary policy in the US in the period from 1969 to 1999. Specifically, they find that a 100 basis point contractionary shock leads to a 4.8% decline in industrial production over 22 months, and inflation declines by 6% over four years. In contrast, traditional indicators tend to produce muted or even counter-intuitive responses, such as the well-known "price puzzle." By controlling for internal expectations, the narrative strategy improves the credibility of causal inference.

These findings not only underscore the empirical relevance of their shock measure but also offer a broader critique of conventional VAR identification strategies. Traditional VAR models typically rely on assumptions of contemporaneous exogeneity and identify shocks through timing restrictions or recursive ordering. However, as Romer & Romer (2004) demonstrate, such approaches often fail to account for the anticipatory nature of policy decisions. When central banks adjust interest rates in response to expected future developments, the resulting shocks in standard VARs may be endogenous, leading to biased or misleading IRFs. By incorporating their refined shock measure into a VAR framework, Romer & Romer (2004) show that the estimated responses of output and inflation become more consistent with theoretical expectations. The resulting impulse responses are stronger, more coherent, and devoid of anomalies such as the price puzzle. This lends credibility to their claim that the weaker or inconsistent effects found in previous empirical studies are largely due to flawed identification of monetary policy shocks. As such, the narrative-based approach provides a compelling benchmark against which conventional VAR-based findings can be assessed.

Despite its advantages, the method employed in Romer & Romer (2004) is resource-intensive and difficult to replicate, especially outside the U.S. context. It requires detailed, high-frequency internal forecasts and meeting documentation, much of which is not publicly available for Brazil. Even if such documents existed, the subjective interpretation of meeting narratives introduces scope for researcher bias and limits replicability. Furthermore, this method excludes potentially important inter-meeting policy moves and may still miss unobserved dimensions of central bank expectations.

In Brazil's case, several obstacles prevent the direct application of this method. First, the necessary internal forecasts and meeting records have not been consistently published. Second, the Brazilian monetary policy framework has been subject to more volatility and structural breaks than that of the U.S., making it difficult to cleanly separate anticipatory responses from exogenous shocks. Finally, the time and data demands of the approach would be considerably higher in a context where transparency is still evolving.

Nonetheless, if data and institutional transparency allowed, applying the Romer & Romer (2004) methodology in Brazil could yield more precise shock identification and, in turn, more accurate estimates of the sacrifice ratio and policy effectiveness. Until such conditions are met, however, the TVP-SVAR-SV model offers a practical and well-founded approach for capturing the effects of monetary policy.

8.3. Partial Conclusion

This section has critically assessed the empirical framework used in the thesis and considered alternative approaches to the identification of monetary policy shocks. The robustness checks indicate that the core findings are largely stable across reasonable changes in model specification - both in terms of variable ordering and exchange rate measurement. While minor variations in magnitude were observed, especially sacrifice ratios, the overall impulse response patterns remain consistent. This strengthens confidence in the reliability of the results obtained in Sections 6 and 7.

At the same time, the discussion highlighted a key limitation of the recursive identification strategy employed in the TVP-SVAR-SV model: its inability to fully account for the forward-looking nature of monetary policy. The narrative-based identification method proposed by Romer & Romer (2004) offers a more precise alternative by isolating truly exogenous shocks. Despite the appeal of this alternative strategy, its application is limited in contexts like Brazil due to institutional and data-related constraints, including the lack of consistently available internal forecasts and central bank meeting records. As such, while narrative identification may yield more precise estimates of policy effects from a theoretical point of view, the TVP-SVAR-SV remains a pragmatic and credible choice given the empirical realities.

In summary, while the TVP-SVAR-SV model is not without limitations, particularly regarding the identification of forward-looking policy shocks, it remains a robust and empirically grounded framework for analysing Brazil's monetary transmission mechanisms. The stability of the core findings across robustness checks and the practical constraints on implementing alternative identification strategies further support its use in this context. With this empirical foundation established, the following section turns to the broader policy implications of the analysis. In particular, it explores how the observed evolution of the sacrifice ratio, the role of external transmission channels, and institutional features of the Brazilian economy inform the design and implementation of effective monetary policy.

9. Policy Implications

This section discusses the policy implications of the empirical findings in this thesis. It focuses on how Brazil's evolving sacrifice ratio, the role of key transmission channels, and the broader institutional setting shape the effectiveness of monetary policy. The discussion is structured around four central themes: i) the importance of transparency and credibility within an inflation-targeting regime, ii) the exchange rate's role in amplifying trade-offs between inflation and output, iii) the influence of global commodity prices, and iv) the interaction between fiscal and monetary regimes.

9.1. Transparency, Credibility, and Inflation Targeting

The steady decline in Brazil's sacrifice ratio over the sample period suggests a gradual improvement in the effectiveness of monetary policy. One key factor that may underlie this development is increased transparency and credibility of the BCB, particularly in the context of the inflation-targeting regime adopted in 1999. As discussed in Section 7, institutional reforms that enhanced transparency likely contributed to anchoring inflation expectations, which, in turn, reduced the output cost of disinflation. This interpretation is consistent with the findings of Chortareas et al. (2002), who demonstrate that forecast transparency and accountability mechanisms significantly lower the sacrifice ratio in OECD countries.

Nevertheless, improvements in credibility are unlikely to have been immediate. Early in the inflation-targeting regime, Brazil experienced high inflation volatility and policy deviations - most notably in 2002, when inflation significantly exceeded the target. These early deviations may have delayed the consolidation of credibility, leading to a more gradual reduction in the sacrifice ratio during the first part of the 2000s.

The broader literature presents mixed evidence on the effect of inflation targeting on monetary policy effectiveness. Gonçalves & Carvalho (2009) find that, for OECD countries, inflation targeting tends to lower the sacrifice ratio, especially in economies with high inflation and low debt levels - both characteristics that make disinflation less costly and encourage adoption of the regime. However, this view has been challenged. Brito (2010) argues that the results in Gonçalves & Carvalho (2009) are not robust, pointing out that they fail to adequately control for macroeconomic conditions or institutional differences. When isolating the effect of inflation targeting itself, Brito (2010) finds little evidence that the regime alone drives disinflation outcomes.

The findings are more nuanced for emerging markets. Lee (2011) examine a range of developing economies using synthetic control methods and find that inflation targeting generally reduces inflation, although the strength of the effect varies significantly across countries. Notably, the study finds no strong evidence that inflation targeting led to lower inflation in Brazil relative to its control group, highlighting that the regime's effectiveness is conditional on institutional preconditions. These include central bank independence, a stable financial system, and adequate technical capacity. Without such foundations, the credibility gains from adopting inflation targeting may remain limited.

The case of Brazil during the global inflation surge in 2021–2022 provides further support for the role of credibility. Despite the severity of the external shock, inflation expectations remained relatively contained, and the sacrifice ratio continued to decline. This pattern mirrors findings from Zlobins (2025), who attributes the low output cost of disinflation in the euro area during the same period to a steeper Phillips curve and a strong, credible policy stance by the ECB. In Brazil, the quick and decisive policy response, combined with earlier transparency reforms, likely helped preserve the central bank's credibility during this challenging period.

Taken together, these findings suggest that while inflation targeting can provide a framework for improving monetary policy effectiveness, its success is highly dependent on the surrounding institutional environment. In Brazil's case, the inflation-targeting regime appears to have become more effective over time, not necessarily because of the regime itself, but because of the institutional credibility gradually built through transparency, accountability, and consistent policy actions. This underscores the importance of viewing inflation targeting not as a final solution, but as part of a broader institutional architecture that must be carefully maintained to ensure effective monetary policy transmission.

9.2. The Role of Exchange Rate in Policy Transmission

One of the more notable findings in this thesis is the substantial improvement in Brazil's sacrifice ratio when the exchange rate channel is removed from the empirical model. This result implies that the exchange rate acts as a complicating factor in the transmission of monetary policy, particularly by worsening the inflation-output trade-off. Specifically, excluding the exchange rate variable results in lower output losses for each unit of disinflation - suggesting that, in Brazil's case, the exchange rate channel introduces inflationary feedback that undermines the effectiveness of interest rate-based policy.

The mechanism behind this inefficiency appears to rest in the behaviour of the BRL in response to monetary tightening. Rather than appreciating in line with textbook open-economy models, the BRL has at times depreciated in response to interest rate hikes. This procyclical exchange rate dynamic may be linked to Brazil's exposure to sovereign risk and capital flight, where higher interest rates signal broader economic fragility rather than stability. As a result, instead of dampening inflation via cheaper imports, monetary tightening may inadvertently raise import prices through currency depreciation. This not only limits the disinflationary impact of policy but also intensifies its contractionary effect on output.

These findings align closely with the existing literature. In their structural model of Brazil's economy, Minella & Souza-Sobrinho (2009) demonstrate that an appreciation of the BRL reduces inflation by lowering import prices but also depresses net exports through higher import volumes and reduced competitiveness of domestic producers. In the long run, they find that the price effects dominate, ultimately reducing output. Their work confirms that the exchange rate significantly influences both inflation and the output gap, reinforcing the importance of correctly modelling this channel in policy analysis.

Similarly, Brandao-Marques et al. (2021) show that in emerging markets, the exchange rate amplifies the pass-through of monetary policy shocks to both inflation and real activity. Their findings suggest that failure to account for exchange rate dynamics leads to underestimating the real costs of disinflation in economies where exchange rate volatility is high. Moreover, Lima et al. (2011) emphasise the dual nature of the exchange rate as both a transmitter and absorber of shocks. They show that the exchange rate in Brazil explains a considerable share of short-term variation in inflation and output and acts as an independent source of volatility in addition to reacting to policy changes.

Together, these studies support the conclusion that the exchange rate is a central feature of Brazil's monetary transmission mechanism. The empirical findings in this thesis support this notion, with the sacrifice ratio falling significantly when this channel is excluded, precisely because the indirect inflationary consequences of exchange rate fluctuations are removed from the system. From a policy design perspective, this implies that monetary authorities in Brazil cannot treat the exchange rate as exogenous or irrelevant. Rather, they must account for its inflationary feedback loops and potentially destabilising influence on output. Greater exchange rate volatility, if left unchecked, can undermine the effectiveness of monetary tightening, leading to higher sacrifice ratios and a less efficient trade-off between inflation control and economic activity.

This underscores the importance of coordinated macroeconomic management in Brazil, where exchange rate movements must be monitored and, where necessary, complemented by fiscal measures or financial regulations to prevent unintended policy spillovers. The BRL's response to interest rate adjustments is not merely a side effect but a crucial determinant of the overall success of monetary policy.

9.3. The Role of Commodity Prices in Policy Transmission

While the exchange rate clearly plays a dominant role in Brazil's monetary transmission mechanism, the impact of commodity prices should not be overlooked. As an emerging economy with substantial dependence on commodity exports, Brazil is inherently vulnerable to commodity price fluctuations, which can shape both inflation dynamics and output volatility. The findings of this thesis suggest that while the exclusion of the commodity price channel from the model does not produce as large a reduction in the sacrifice ratio as removing the exchange rate channel, it still affects the inflation-output trade-off in meaningful ways.

The impulse response analysis supports this view. Shocks to commodity prices show a relatively muted and inconsistent effect on the output gap but generate a more pronounced and statistically significant effect on inflation. Specifically, increases in global commodity prices tend to raise domestic inflation, likely through cost-push mechanisms affecting food and energy prices. However, the link to output is less direct and often overshadowed by external factors, such as international liquidity conditions or domestic absorption capacity.

Additionally, Drechsel et al. (2019) offer a theoretical explanation for the output volatility that can accompany commodity price cycles in small open economies. Their model incorporates a financial channel in which commodity booms loosen borrowing constraints for producers, leading to inefficient sectoral reallocation and increased output volatility. Because their framework lacks the "divine coincidence", where stabilizing inflation also stabilizes output, policymakers are forced to weigh inflation control against real distortions. They find that optimal monetary policy in such environments calls for exchange rate appreciation and higher interest rates during commodity booms, especially when financial channels are strong. Although Brazil is a larger and more complex economy than those in Drechsel's sample, their findings still offer a useful perspective: Brazil pursued expansionary policies during its commodity boom in the early 2010s and tightened policy after the 2014 bust - potentially amplifying the downturn. This procyclical response runs counter to Drechsel's recommendations and may have increased the macroeconomic costs of adjustment.

These dynamics are further reflected in empirical studies. da Silva Souza & Fry-McKibbin (2021) argue that commodity demand, rather than commodity prices per se, plays a more influential role in shaping macroeconomic outcomes in emerging markets like Brazil. Their findings indicate that when commodity demand is included in the model, the impact of monetary policy is dampened - suggesting that strong external demand for commodities can blunt the effect of domestic rate changes. They also find that global liquidity shocks can lead to rising commodity prices, which appreciate the domestic currency, prompting the central bank to lower interest rates and support domestic demand. This interaction illustrates the complexity of the commodity price channel, especially when combined with exchange rate effects.

de Melo (2013) adds further nuance by highlighting the asymmetric inflationary impact of commodity prices in emerging markets. He finds that these economies tend to suffer more from commodity-driven inflation due to higher weights of food and energy in their consumption baskets and relatively lower energy efficiency. In the case of Brazil, this vulnerability is partially offset by the fact that strong commodity exports contribute to capital inflows, which can appreciate the currency and dampen imported inflation. This two-way effect, where commodity prices both raise domestic costs and attract foreign exchange, makes the net policy implication less straight forward.

The evidence presented in this thesis supports these mixed findings. While commodity price shocks are clearly inflationary, their effects on output are weak and often statistically insignificant. Moreover, some of the inflationary pressure from commodities may be neutralized by exchange rate appreciation, further complicating the transmission path. This makes it difficult to assign a singular policy recommendation to the commodity price channel, as its effects depend heavily on external conditions and their interaction with Brazil's financial and trade structures.

In sum, while commodity prices are less central to Brazil's monetary transmission than the exchange rate, they still matter - particularly through their influence on inflation and their interaction with the exchange rate. Their indirect role in shaping policy responses and credibility means they cannot be ignored, but any response to commodity-driven shocks must be carefully calibrated. For policymakers, this highlights the need for improved real-time monitoring of global commodity markets and better modelling of their pass-through effects. However, given the ambiguous evidence on their output effects, further research is needed before firm conclusions can be drawn regarding optimal policy design.

9.4. Fiscal-Monetary Regimes and Coordination

The interaction between fiscal and monetary authorities plays a critical role in shaping the macroeconomic environment within which central banks operate. As highlighted by Gibbs & Xin (2024), the effectiveness of disinflationary policy, and thus the sacrifice ratio, can vary substantially depending on whether an economy is operating under a monetary-led or a fiscal-led regime. In monetary-led regimes, where the central bank maintains independence and fiscal authorities adjust passively to ensure debt sustainability, disinflation tends to be less costly. Expectations of future inflation are anchored, and anticipated disinflation puts immediate downward pressure on current inflation, often requiring smaller policy interventions. In contrast, under fiscal-led regimes, the central bank's ability to control inflation may be compromised by fiscal dominance, where government debt sustainability takes precedence over price stability. Here, the sacrifice ratio becomes more variable and often higher, as monetary tightening has to counteract expansionary fiscal signals.

In Brazil's case, empirical studies by Scaramuzzi & Muinhos (2024) and Moreira et al. (2021) reveal that the policy regime has not been stable over the sample period. From 2002 until around 2013, Brazil was predominantly in a monetary-led regime, followed by a shift to fiscal-led policies between 2013 and 2016, a brief return to monetary dominance until 2019, and then another transition to fiscal-led conditions during the COVID-19 period. This regime instability complicates the interpretation of monetary policy outcomes, as shifting fiscal stances can obscure the effectiveness of interest rate changes and dampen the credibility of inflation-targeting commitments.

Interestingly, the thesis findings show that Brazil's sacrifice ratio began to decline most significantly during 2013–2016 - a period that both Scaramuzzi & Muinhos (2024) and Moreira et al. (2021) classify as fiscally led. This might seem counter-intuitive, but it suggests that while regime type matters, other factors such as transparency, global economic conditions, or central bank communication strategies also play a role. More importantly, it underscores that the credibility of a regime, not just its classification, determines policy effectiveness. A regime that signals conflicting objectives between fiscal and monetary authorities may confuse market expectations and undermine disinflation efforts, regardless of whether it is formally labelled "monetary-led" or "fiscal-led."

The findings from Gibbs & Xin (2024) further emphasize that coordination between monetary and fiscal policies is key to reducing the output cost of disinflation. In well-anticipated disinflation episodes, even fiscal-led regimes can produce relatively low sacrifice ratios - provided that policy changes are credible and communicated clearly. However, when fiscal responses are inconsistent or debt sustainability is questioned, real interest rates must rise more sharply to achieve the same disinflationary effect, raising output losses in the process.

For Brazil, the practical implication is that maintaining clear and credible institutional boundaries between fiscal and monetary authorities is essential - but so too is their coordination. Enhancing fiscal transparency, enforcing fiscal rules, and aligning budgetary actions with monetary policy objectives could strengthen policy credibility and lower disinflation costs. In a context where regime shifts are frequent and often politically driven, institutional reforms that promote stability and consistency are likely to yield longer-term improvements in the effectiveness of monetary policy. As a result, in order to reduce the sacrifice ratio in Brazil further, it will require not just central bank independence, but a stable and coherent policy framework in which fiscal and monetary objectives are mutually reinforcing.

9.5. Partial Conclusion

The empirical analysis in this thesis offers several key policy insights for improving the effectiveness of monetary policy in Brazil. First, while inflation targeting has likely contributed to a declining sacrifice ratio over time, its success has depended critically on the institutional environment. The evidence suggests that increased transparency, policy consistency, and credibility, rather than the targeting framework alone, have helped anchor inflation expectations and reduce the cost of disinflation.

Second, the exchange rate emerges as a central channel in Brazil's monetary transmission mechanism, with procyclical currency movements often undermining policy effectiveness. The finding that removing the exchange rate channel improves the sacrifice ratio highlights the need for policymakers to better account for its destabilising potential. Managing exchange rate volatility, potentially with support from aligned fiscal policy and financial regulation, should be a priority for improving monetary transmission.

Third, while commodity prices clearly affect inflation, their effects on output are weaker and more ambiguous. Nonetheless, given Brazil's exposure to global commodity cycles, these shocks interact with exchange rates and policy responses in complex ways. Better monitoring and modelling of commodity pass-through effects will be necessary for more informed and adaptive policymaking.

Finally, the interaction between fiscal and monetary regimes has important implications for policy credibility and disinflation costs. While regime shifts have been a feature of Brazil's recent history, credible coordination between monetary and fiscal authorities, grounded in transparent rules and clear communication, can help reduce uncertainty and improve macroeconomic outcomes.

Taken together, these findings highlight that improving the effectiveness of monetary policy in Brazil requires more than just technical refinements to interest rate management. It depends on strengthening institutional credibility, managing transmission asymmetries, and creating greater coherence between fiscal and monetary policy objectives.

10. Conclusion

This thesis set out to assess how transmission channels, specifically the exchange rate and global commodity prices, shape the effectiveness of monetary policy in Brazil, with a particular emphasis on the inflation-output trade-off. Using a TVP-SVAR-SV model, the analysis covered the period from 2000 to 2024 and compared a baseline model with two alternative specifications excluding each of the channels. The findings highlight that the transmission of monetary policy shocks in Brazil is both dynamic and highly sensitive to external conditions.

Over the period examined, monetary policy shocks have consistently affected both inflation and output, though the strength and nature of these effects have evolved considerably. In the early 2000s, disinflation required substantial output sacrifices, reflecting a relatively inefficient policy environment. However, the effectiveness of monetary policy has improved in later years, as evidenced by declining sacrifice ratios. This evolution appears to be closely linked to institutional strengthening, including enhanced credibility of the inflation-targeting regime, greater policy transparency, and improved communication strategies by the BCB. The analysis thus confirms that the inflation-output relationship has not remained static, but has become more favourable to policymakers over time.

A key factor influencing these outcomes is the role of the exchange rate channel. Rather than supporting the monetary transmission, the exchange rate has often acted as a complicating factor. The results indicate that monetary tightening has, in several episodes, coincided with depreciation rather than appreciation of the BRL - thereby amplifying inflationary pressures and increasing the output cost of disinflation. When the exchange rate channel is excluded from the model, the estimated sacrifice ratio improves, suggesting that exchange rate volatility has frequently undermined the intended effects of policy. This highlights the importance of managing exchange rate expectations and volatility, particularly in an economy with high pass-through effects and open capital accounts.

In contrast, the commodity price channel exhibits a more nuanced influence. While commodity price fluctuations introduce exogenous shocks that complicate the policymaker's task, especially in periods of global volatility, they have also, in recent years, contributed to output stabilization. Rising global commodity prices have supported Brazil's export revenues and domestic demand, which in turn has softened the output cost of monetary tightening. Although excluding this channel improves the sacrifice ratio in earlier years, its inclusion becomes beneficial in the later sample period. This suggests that Brazil's commodity dependence, while a source of external vulnerability, can also serve as a buffer when global conditions are favourable.

Taken together, the results show that the channels plays an important role in Brazil's monetary policy trade-offs. The exchange rate channel has often imposed additional costs by transmitting depreciation-induced inflation, particularly in times of fiscal stress or global financial tightening. Meanwhile, the commodity price channel has played a dual role - initially amplifying volatility but more recently supporting output during disinflationary episodes. The broader conclusion is that while Brazil's monetary policy has become more effective over time, its effectiveness remains contingent on external conditions and the institutional capacity to manage them.

In answering the central research question "How do the exchange rate and commodity price channels affect the effectiveness of monetary policy in Brazil, particularly in terms of the inflation-output trade-off?", it is clear that both channels significantly shape the inflation-output trade-off. The exchange rate tends to worsen this trade-off, whereas commodity prices can either mitigate or amplify it depending on global trends. Policymakers in Brazil must therefore remain attentive to the evolving nature of these channels and design policy frameworks that are not only internally consistent but also resilient to external shocks. Strengthening communication, reinforcing credibility, and enhancing coordination between fiscal and monetary authorities will be critical to sustaining the gains achieved and further improving the effectiveness of monetary policy in an open and commodity-reliant economy.

11. Recommendations for Future Research

This section outlines several directions for future research that could build on and extend the analysis conducted in the thesis. These suggestions aim to deepen the understanding of Brazil's monetary policy transmission and broaden the empirical relevance of the findings.

One natural extension would involve rethinking the model's external sector representation. While this thesis focused on the exchange rate and commodity prices as key external transmission channels, additional variables could offer complementary perspectives. For instance, incorporating the VIX index, a proxy for global financial uncertainty, could help capture the role of risk sentiment and capital flow volatility in shaping monetary dynamics. Similarly, including a measure of China's industrial production may offer insight into Brazil's exposure to fluctuations in external real demand, especially given China's position as a major trade partner (The Obsevatory of Economic Complexity, 2025). These additions would allow for a richer analysis of how global shocks propagate through Brazil's economy, particularly under different exchange rate regimes and macroeconomic conditions.

Another extension lies in refining the identification of monetary policy shocks. As discussed in Section 8, recursive identification strategies may conflate endogenous policy responses with genuine exogenous shocks. Future research could explore the use of narrative-based or high-frequency identification approaches, such as those leveraging policy announcement windows, central bank minutes, or forecast errors, to more accurately isolate unexpected monetary policy actions. Embedding such externally identified shocks within a TVP-SVAR-SV framework could enhance causal interpretation and yield sharper insights into the evolving nature of policy effectiveness.

Lastly, expanding the scope of analysis beyond Brazil to a panel of emerging market economies could generate comparative insights. This would not only test the generalizability of the findings, but also allow for the identification of regional patterns, institutional effects, and policy-specific nuances in transmission mechanisms. Such cross-country analysis could be particularly valuable for understanding how structural characteristics, such as fiscal credibility, inflation targeting regimes, or capital account openness, interact with external shocks and monetary policy responses.

In sum, these extensions would offer valuable opportunities to explore the complexity of monetary transmission in a globalized, dynamic context - pushing beyond the limitations of a single-country model while preserving the empirical strengths of the current approach.

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A. List of Abbreviations

BCB: Banco Central do Brasil

BRL: Brazilian Real

CPI: Consumer Price Index

ECB: European Central Bank

ESS: Effective Sample Size

FED: Federal Reserve

FOMC: Federal Open Market Committee

FRED: Federal Reserve Economic Data

GDP: Gross Domestic Product

HP Filter: Hodric Prescott Filter

IMF: International Monetary Fund

IPCA: National Consumer Price Index

IRF: Impulse Response Function

IS: Investment-Saving

MCMC: Markov Chain Monte Carlo

MLE: Maximum Likelihood Estimation

OECD: The Organization for Economic Cooperation and Development

OLS: Ordinary Least Squares

SR: Sacrifice Ratio

Selic rate: Sistema Especial de Liquidação e de Custódia interest rate

SVAR: Structual Vector Autoregression

TVP-SVAR-SV: Time-Varying Parameter Structural Vector Autoregression with Stochastic Volatility

US: United States

USD: United States Dollar

VAR: Vector Autoregression

B. Econometric Methods

Appendix B elaborates on the econometric methods used in the project in connection with the empirical analysis and its results. Specifically, Appendix B.1 introduces the principles of Markov Chain Monte Carl (MCMC) estimation while Appendix B.1.1 introduces a generic example of the Gibbs Sampling algorithm.

B.1. Markov Chain Monte Carlo

Markov Chain Monte Carlo (MCMC) estimation is valuable in Bayesian inference, particularly as it enables the estimation of posterior distributions that are otherwise difficult to compute analytically. This is especially useful in cases where direct computation of the posterior distribution is infeasible due to its high-dimensional complexity. By generating random samples from the target distribution, MCMC provides an efficient method for approximating probability distributions.

MCMC combines two fundamental concepts: Monte Carlo methods and Markov chains. Monte Carlo sampling involves estimating the characteristics of a probability distribution by drawing a large number of random samples and computing summary statistics, such as the mean and variance. This approach is computationally advantageous, as it allows for the estimation of distributional properties without requiring closed-form solutions. The benefits of this approach are particularly significant when the underlying distribution is complex and difficult to manipulate algebraically, yet generating random samples is computationally feasible. Rather than solving distribution equations directly, Monte Carlo estimates key properties, such as the mean or variance, based on the drawn samples, making the method especially powerful in high-dimensional settings.

A Markov-Chain, on the other hand, refers to a sequential sampling process in which each new sample depends only on the immediate preceding sample, satisfying the Markov property. This implies that while each sample is conditionally dependent on the previous one, it remains independent of all earlier samples beyond the most recent step. The resulting sequence of dependent samples forms a stochastic process that, under appropriate conditions, converges to the target distribution, thereby enabling accurate approximation of posterior distributions.

MCMC is particularly beneficial in Bayesian inference, as it makes it possible to work with posterior distributions that are analytically complex. Since Bayesian inference updates prior beliefs using data to form a posterior distribution, MCMC plays a crucial role in approximating aspects of the posterior that cannot be directly computed. In cases where an analytical expression for the likelihood is unavailable, MCMC generates a sequence of samples from the posterior distribution, allowing for inference based on properties such as the mean, range, and variance of these samples (van Ravenzwaaij et al., 2016, pp. 143-144).

B.1.1. Gibbs Sampling

Gibbs sampling is an MCMC approach that is particular effective when parameters exhibit strong correlations. In such cases, standard MCMC methods may lead to extremely slow convergence of sampling chains or even non-convergence. The Gibbs sampler mitigates this issue by employing a blocking strategy, which divides the parameter space into smaller subsets and samples from these blocks sequentially (van Ravenzwaaij et al., 2016, pp. 147-148). This approach allows for sampling from the lower-dimensional conditional posterior distributions of the individual parameters rather than directly drawing from the high-dimensional joint posterior of the entire parameter space. By estimating each parameter separately, Gibbs sampling improves computational efficiency and facilitates convergence (Primiceri, 2005, p. 826).

For example, consider a parameter vector θ that is divided into r blocks, represented as $\theta = (\theta_1, ..., \theta_r)$. Given the current state of the parameter vector at iteration t, denoted as $\theta^t = (\theta_1^t, ..., \theta_r^t)$, the updated state θ^{t+1} is obtained through the following iterative sampling process:

$$\text{draw } \theta_1^{t+1} \text{ from } h(\theta_1^{t+1}|\theta_2^t, ..., \theta_r^t) \tag{B.1}$$

$$\text{draw } \theta_2^{t+1} \text{ from } h(\theta_2^{t+1}|\theta_1^{t+1}, ..., \theta_3^t, +..., \theta_r^t) \tag{B.2}$$

$$\vdots$$

$$\text{draw } \theta_r^{t+1} \text{ from } h(\theta_r^{t+1}|\theta_1^{t+1}, ..., \theta_{r-1}^{t+1}) \tag{B.3}$$

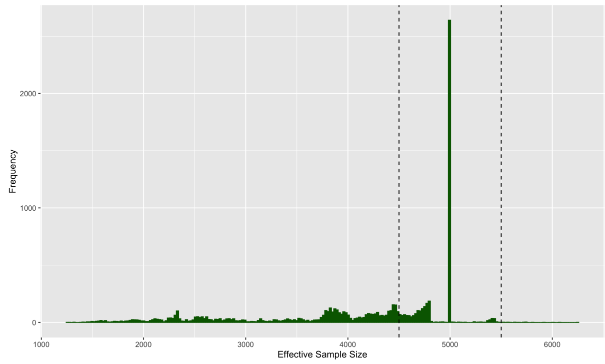
The Gibbs sampler sequentially updates each of the r parameter blocks by drawing from their respective conditional posterior distributions, given the most recent values of the remaining parameters. This blocking mechanism ensures that each conditional distribution is lower-dimensional and thus easier to sample from than the full joint posterior. Since each update of a parameter block is conditioned on the most recent values of the other blocks, this process effectively constructs a sequence of dependent samples that collectively approximate the target posterior distribution.

Each complete cycle through all parameter blocks constitutes a single iteration of the Gibbs sampler. Over repeated iterations, the generated samples approximate the joint posterior distribution by iteratively conditioning on updated parameter values. By repeatedly updating each parameter block while conditioning on the most recent values of the others, the Gibbs sampler gradually converges to an approximation of the joint posterior distribution. Under appropriate regularity conditions, the Gibbs sampler ensures convergence to the target posterior distribution (Gelfand, 2000, pp. 1301-1302).

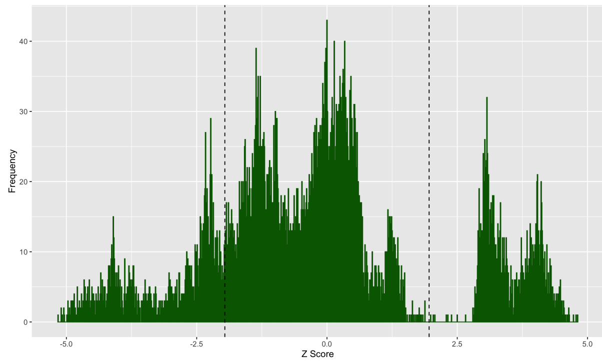
C. Diagnostic Results

Figure C.1: Diagnostic Results for the Baseline Model

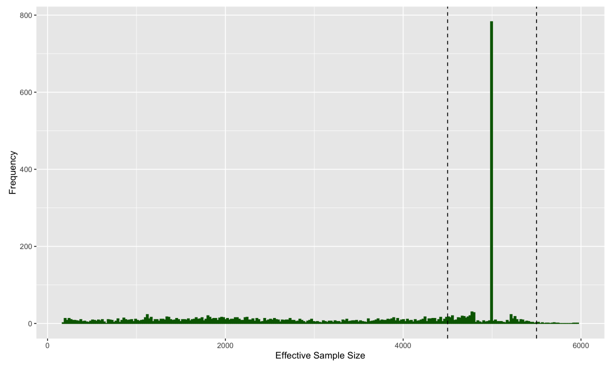
(a) Effective Sample Size for B_t



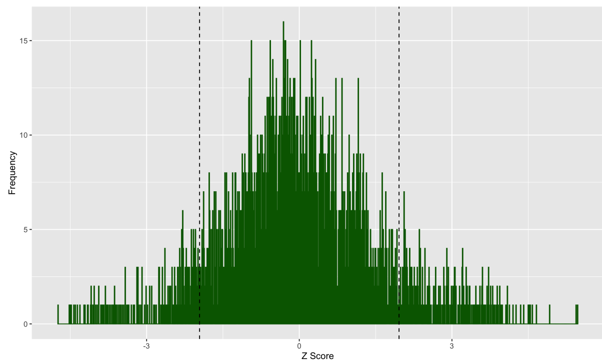
(b) Geweke's Convergence Diagnostic for B_t



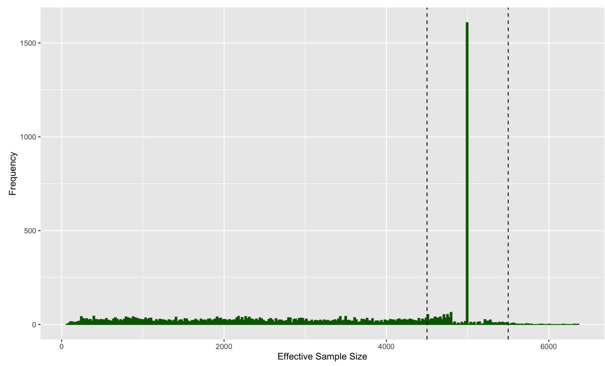
(c) Effective Sample Size for A_t



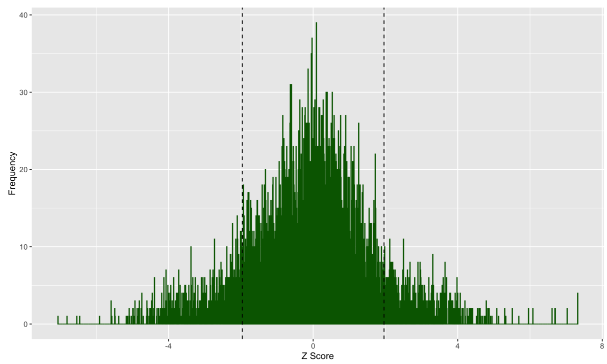
(d) Geweke's Convergence Diagnostic for A_t



(e) Effective Sample Size for Σ_t



(f) Geweke's Convergence Diagnostic for Σ_t

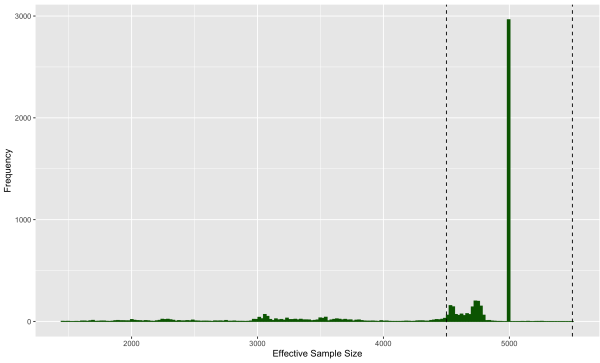


Note: Figures C.1a, C.1c and C.1e illustrate the estimated EES for the baseline model of all estimates of the coefficients given by the matrices B_t, the contemporaneous effects given by the matrices A_t, and the variance-covariance matrices of the error terms Σ_t, respectively for every point in time. In the figures, two horizontal lines is included, which shows the tolerance for deviations between the estimated effective sample size and the raw sample size, corresponding to a 10% deviation from the raw sample size. Meanwhile, Figures C.1b, C.1d and C.1f illustrate the Z-score of Geweke's convergence diagnostics for B_t, A_t and Σ_t, respectively, at every point in time. In the figures, the critical values of the standard normal distribution of ± 1.96 is included to illustrate whether the diagnostic holds for the estimated parameter.

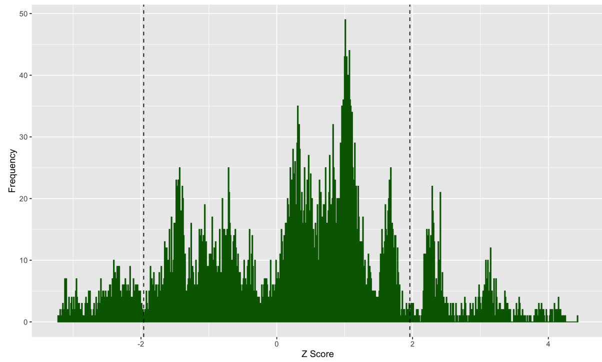
Source: Own presentation of data collected from Banco Central do Brasil (2025a), Banco Central do Brasil (2025c), FRED (2025a), FRED (2025c), FRED (2025d), FRED (2025e), and World Bank Group (2025), compiled as indicated in Table 4.1 and processed in accordance with the methodology in Section 5.

Figure C.2: Diagnostic Results for the Model Excluding Exchange Rate

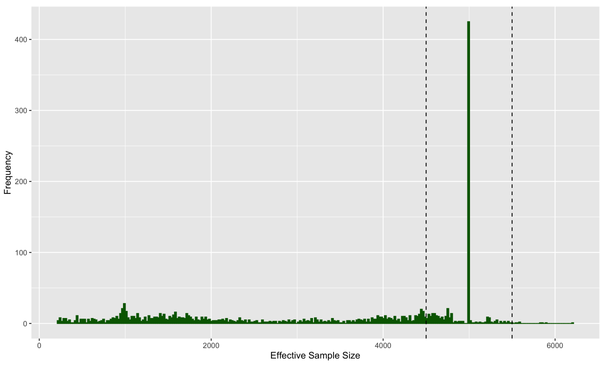
(a) Effective Sample Size for B_t



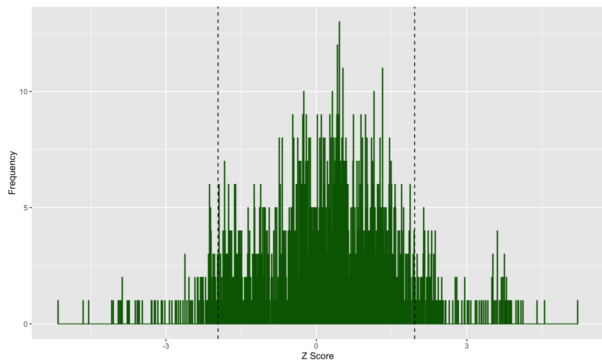
(b) Geweke's Convergence Diagnostic for B_t



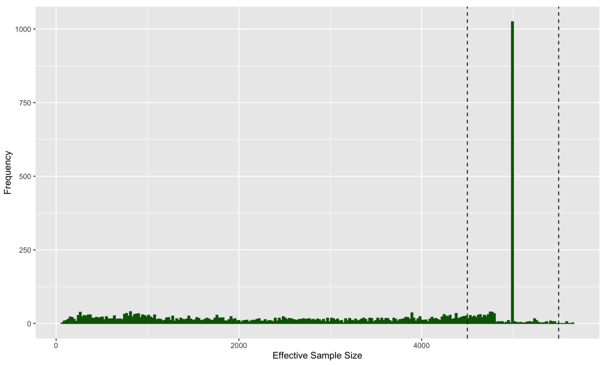
(c) Effective Sample Size for A_t



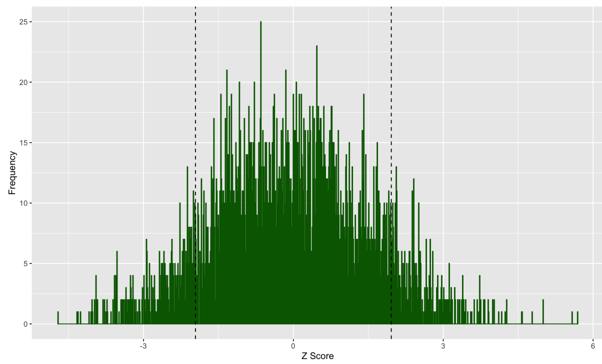
(d) Geweke's Convergence Diagnostic for A_t



(e) Effective Sample Size for Σ_t



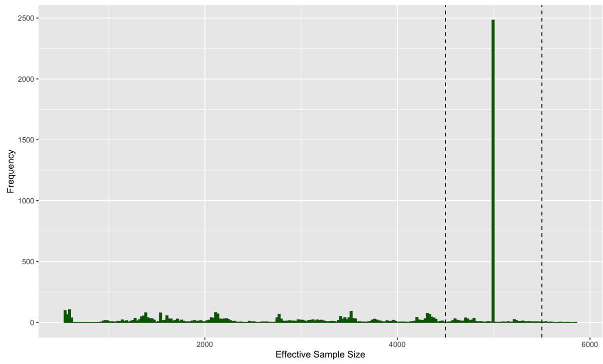
(f) Geweke's Convergence Diagnostic for Σ_t



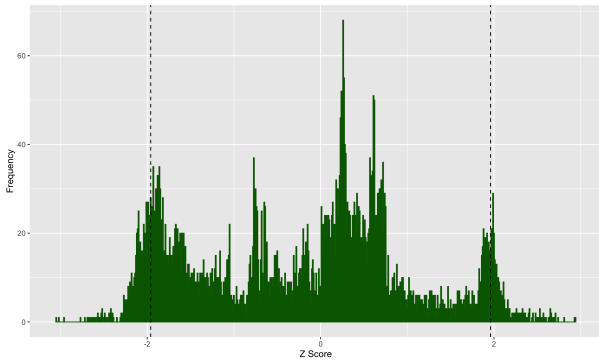
Note: Figures C.1a, C.1c and C.1e illustrate the estimated EES for the model with no exchange rate of all estimates of the coefficients given by the matrices B_t, the contemporaneous effects given by the matrices A_t, and the variance-covariance matrices of the error terms Σ_t, respectively for every point in time. In the figures, two horizontal lines is included, which shows the tolerance for deviations between the estimated effective sample size and the raw sample size, corresponding to a 10% deviation from the raw sample size. Meanwhile, Figures C.1b, C.1d and C.1f illustrate the Z-score of Geweke's convergence diagnostics for B_t, A_t and Σ_t, respectively, at every point in time. In the figures, the critical values of the standard normal distribution of ± 1.96 is included to illustrate whether the diagnostic holds for the estimated parameter.
Source:Own presentation of data collected from Banco Central do Brasil (2025a), Banco Central do Brasil (2025c), FRED (2025c), FRED (2025d), FRED (2025e), and World Bank Group (2025), compiled as indicated in Table 4.1 and processed in accordance with the methodology in Section 5.

Figure C.3: Diagnostic Results for the Model Excluding Commodity Prices

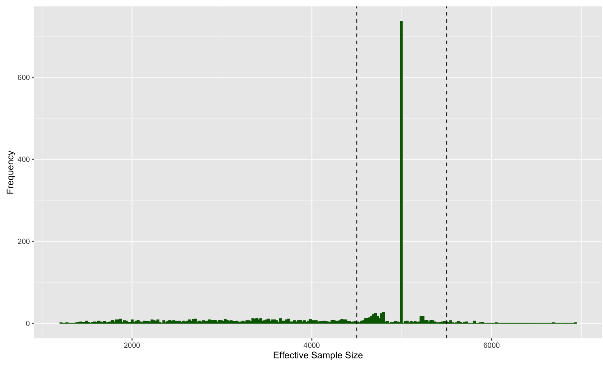
(a) Effective Sample Size for B_t



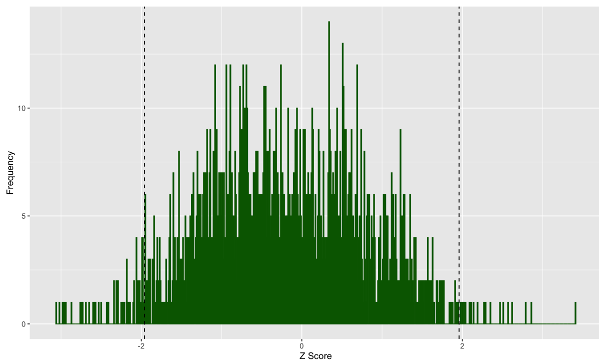
(b) Geweke's Convergence Diagnostic for B_t



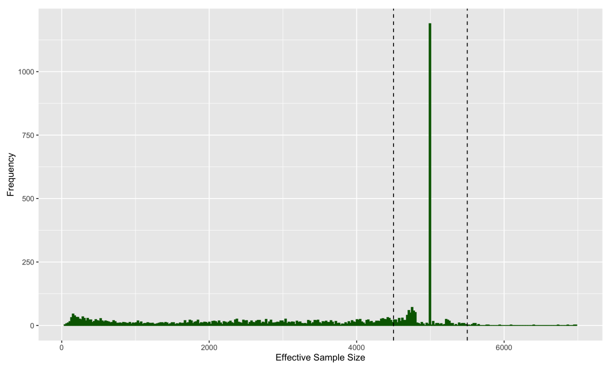
(c) Effective Sample Size for A_t



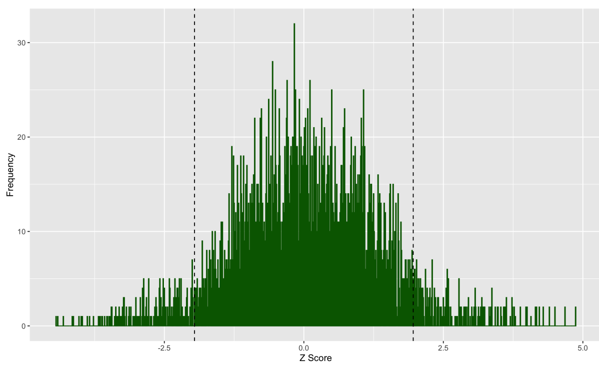
(d) Geweke's Convergence Diagnostic for A_t



(e) Effective Sample Size for Σ_t



(f) Geweke's Convergence Diagnostic for Σ_t



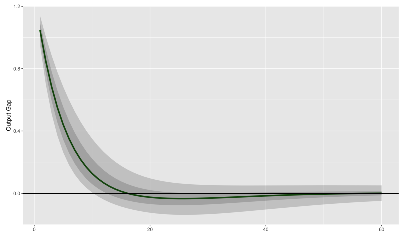
Note: Figures C.1a, C.1c and C.1e illustrate the estimated EES for the model with no commodity prices of all estimates of the coefficients given by the matrices B_t, the contemporaneous effects given by the matrices A_t, and the variance-covariance matrices of the error terms Σ_t, respectively for every point in time. In the figures, two horizontal lines is included, which shows the tolerance for deviations between the estimated effective sample size and the raw sample size, corresponding to a 10% deviation from the raw sample size. Meanwhile, Figures C.1b, C.1d and C.1f illustrate the Z-score of Geweke's convergence diagnostics for B_t, A_t and Σ_t, respectively, at every point in time. In the figures, the critical values of the standard normal distribution of ± 1.96 is included to illustrate whether the diagnostic holds for the estimated parameter.
Source: Own presentation of data collected from Banco Central do Brasil (2025a), Banco Central do Brasil (2025c), FRED (2025a), FRED (2025c), and FRED (2025d), compiled as indicated in Table 4.1 and processed in accordance with the methodology in Section 5.

D. Impulse Response Functions

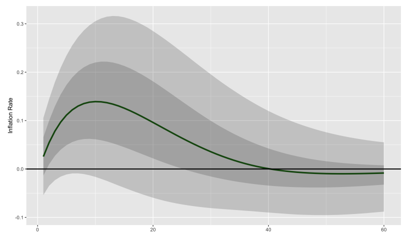
D.1. Baseline Model

Figure D.1: Time-Invariant IRFs in the Baseline Model

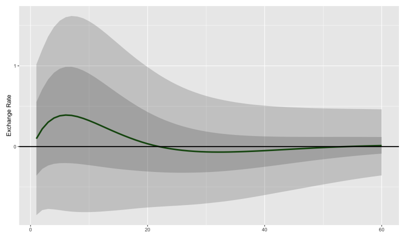
(a) $\varepsilon_{\hat{y}} \uparrow \rightarrow \hat{y}$



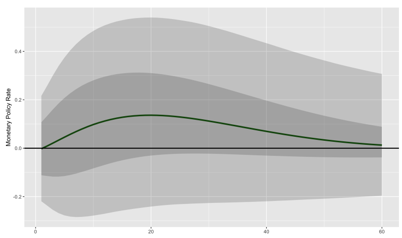
(b) $\varepsilon_{\hat{y}} \uparrow \rightarrow \pi$



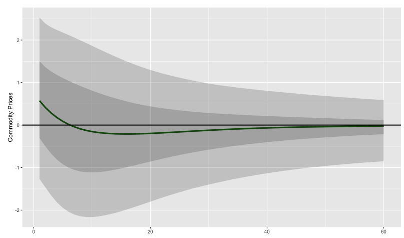
(c) $\varepsilon_{\hat{y}} \uparrow \rightarrow ex$



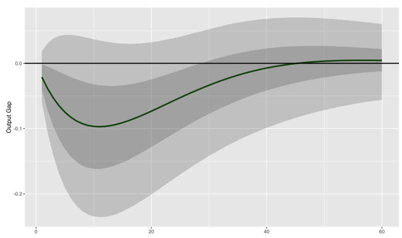
(d) $\varepsilon_{\hat{y}} \uparrow \rightarrow i$



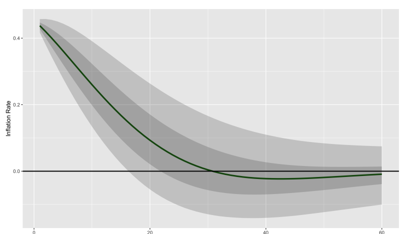
(e) $\varepsilon_{\hat{y}} \uparrow \rightarrow \psi$



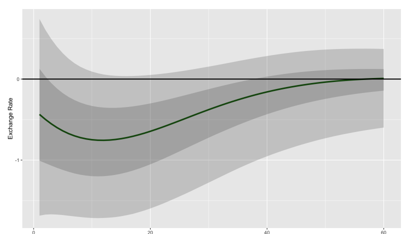
(f) $\varepsilon_{\pi} \uparrow \rightarrow \hat{y}$



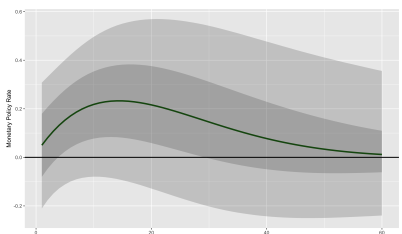
(g) $\varepsilon_{\pi} \uparrow \rightarrow \pi$



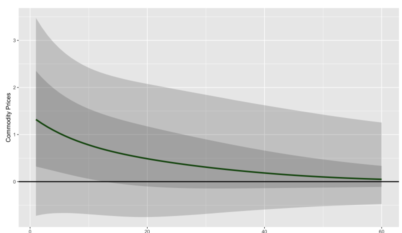
(h) $\varepsilon_{\pi} \uparrow \rightarrow ex$



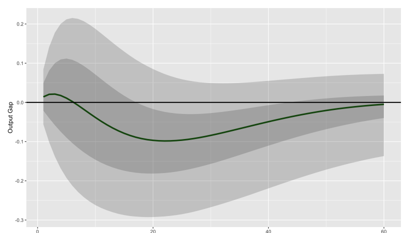
(i) $\varepsilon_{\pi} \uparrow \rightarrow i$



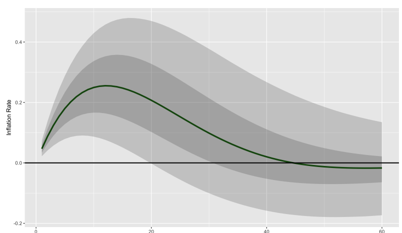
(j) $\varepsilon_{\pi} \uparrow \rightarrow \psi$



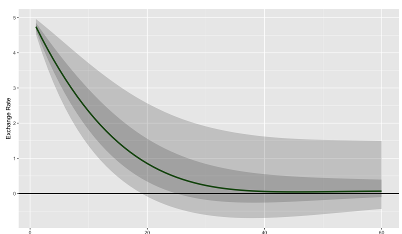
(k) $\varepsilon_{ex} \uparrow \rightarrow \hat{y}$



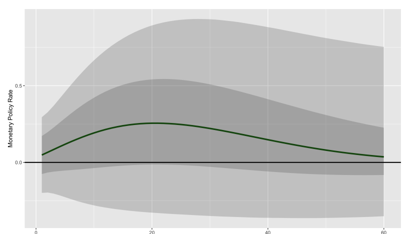
(l) $\varepsilon_{ex} \uparrow \rightarrow \pi$



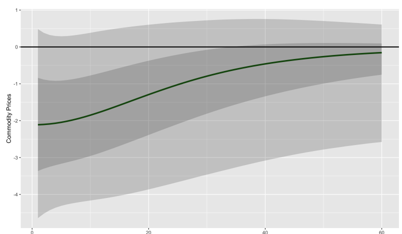
(m) $\varepsilon_{ex} \uparrow \rightarrow ex$



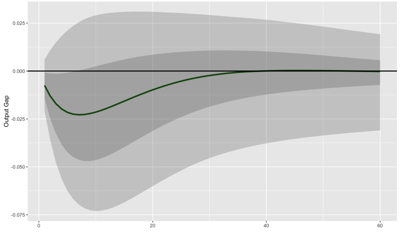
(n) $\varepsilon_{ex} \uparrow \rightarrow i$



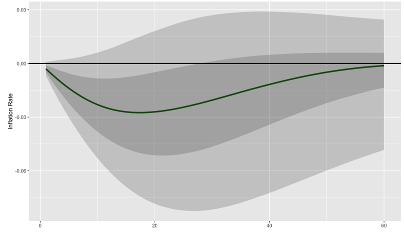
(o) $\varepsilon_{ex} \uparrow \rightarrow \psi$



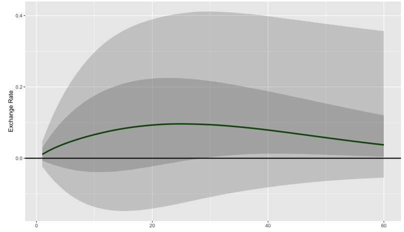
(p) $\varepsilon_i \uparrow \rightarrow \hat{y}$



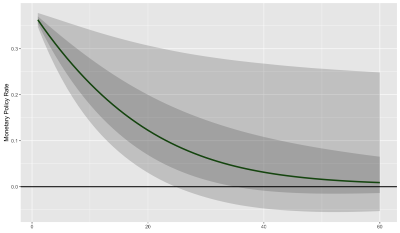
(q) $\varepsilon_{\hat{i}} \uparrow \rightarrow \pi$



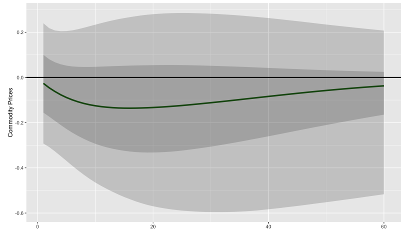
(r) $\varepsilon_i \uparrow \rightarrow ex$



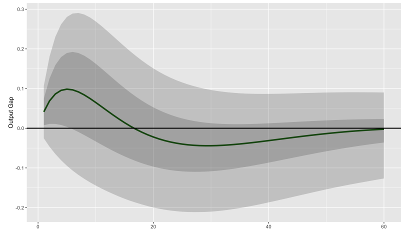
(s) $\varepsilon_i \uparrow \rightarrow i$



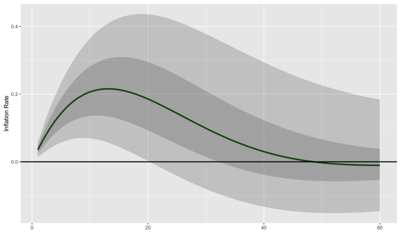
(t) $\varepsilon_i \uparrow \rightarrow \psi$



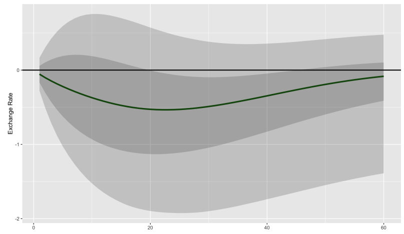
(u) $\varepsilon_\psi \uparrow \rightarrow \hat{y}$



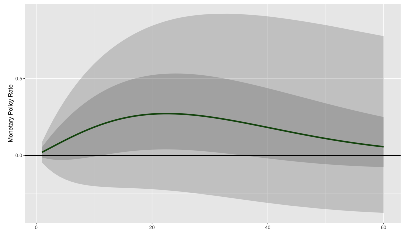
(v) $\varepsilon_\psi \uparrow \rightarrow \pi$



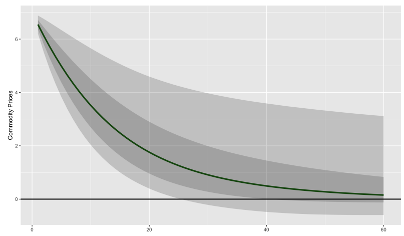
(w) $\varepsilon_\psi \uparrow \rightarrow ex$



(x) $\varepsilon_\psi \uparrow \rightarrow i$



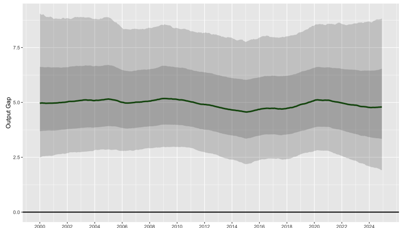
(y) $\varepsilon_\psi \uparrow \rightarrow \psi$



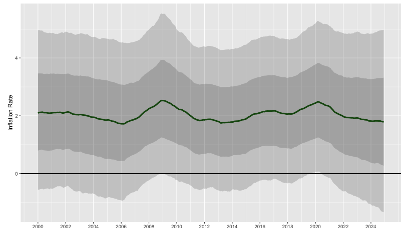
Note: The figure presents the impulse response effects of an output gap shock ($\varepsilon_{\hat{y}}$), inflation rate shock (ε_π), exchange rate shock (ε_{ex}), monetary policy rate shock (ε_i), and commodity price shock (ε_ψ) on the output gap ($\hat{y}$), inflation rate (π), exchange rate (ex), monetary policy rate (i), and commodity prices (ψ) in the baseline model. For each impulse-response pair, the time-invariant average impulse response over a 60-month horizon is displayed, summarizing the IRF estimates across all time points. All panels include the 95% and 68% credible intervals.
Source: Own presentation of data collected from Banco Central do Brasil (2025a), Banco Central do Brasil (2025c), FRED (2025a), FRED (2025c), FRED (2025d), FRED (2025e), and World Bank Group (2025), compiled as indicated in Table 4.1 and processed in accordance with the methodology in Section 5.

Figure D.2: Accumulated Time-Varying IRFs in the Baseline Model

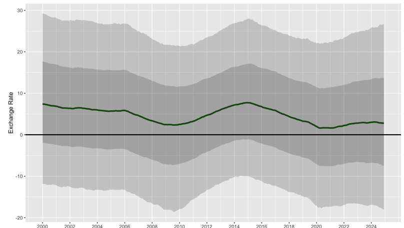
(a) $\varepsilon_{\hat{y}} \uparrow \rightarrow \hat{y}$



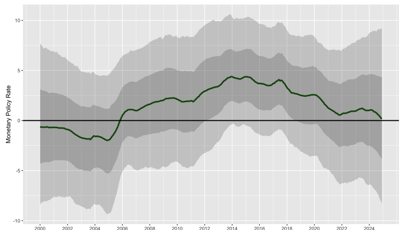
(b) $\varepsilon_{\hat{y}} \uparrow \rightarrow \pi$



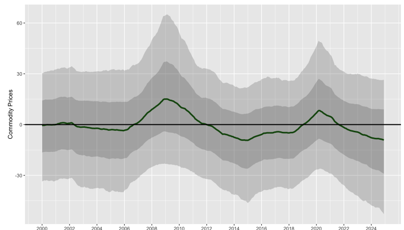
(c) $\varepsilon_{\hat{y}} \uparrow \rightarrow ex$



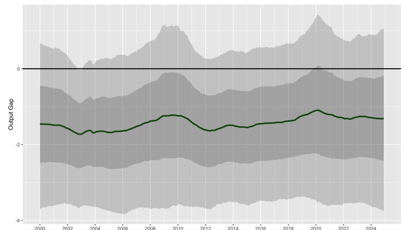
(d) $\varepsilon_{\hat{y}} \uparrow \rightarrow i$



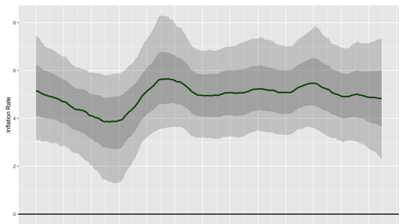
(e) $\varepsilon_{\hat{y}} \uparrow \rightarrow \psi$



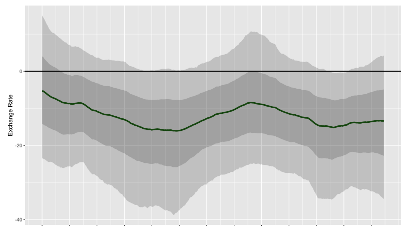
(f) $\varepsilon_{\pi} \uparrow \rightarrow \hat{y}$



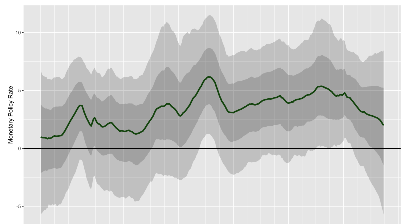
(g) $\varepsilon_{\pi} \uparrow \rightarrow \pi$



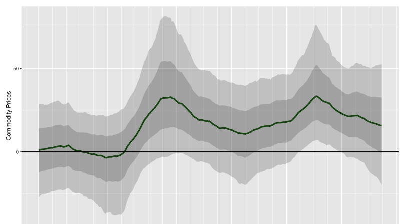
(h) $\varepsilon_{\pi} \uparrow \rightarrow ex$



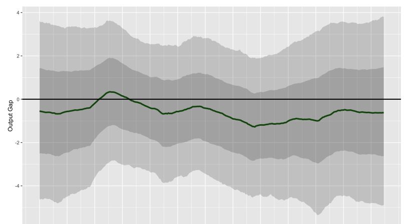
(i) $\varepsilon_{\pi} \uparrow \rightarrow i$



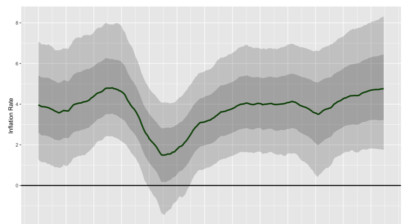
(j) $\varepsilon_{\pi} \uparrow \rightarrow \psi$



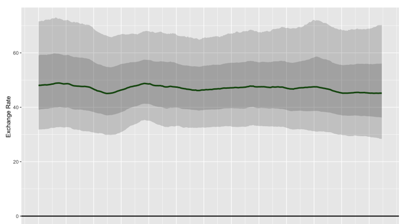
(k) $\varepsilon_{ex} \uparrow \rightarrow \hat{y}$



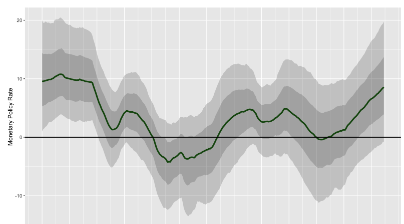
(l) $\varepsilon_{ex} \uparrow \rightarrow \pi$



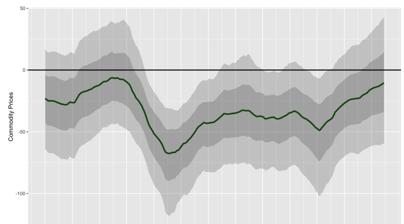
(m) $\varepsilon_{ex} \uparrow \rightarrow ex$



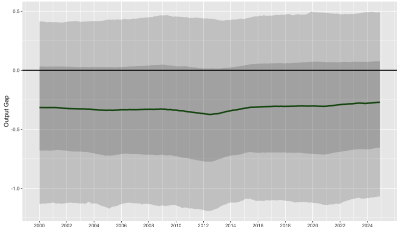
(n) $\varepsilon_{ex} \uparrow \rightarrow i$



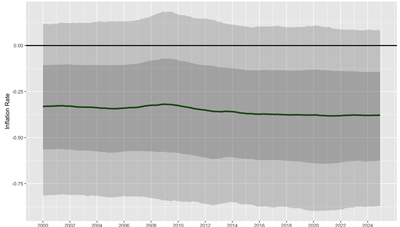
(o) $\varepsilon_{ex} \uparrow \rightarrow \psi$



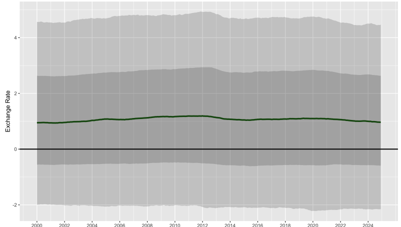
(p) $\varepsilon_i \uparrow \rightarrow \hat{y}$



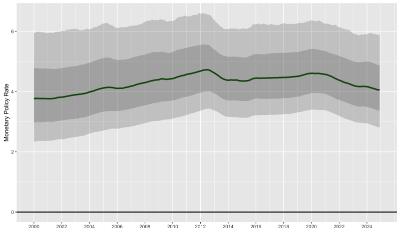
(q) $\varepsilon_{\hat{i}} \uparrow \rightarrow \pi$



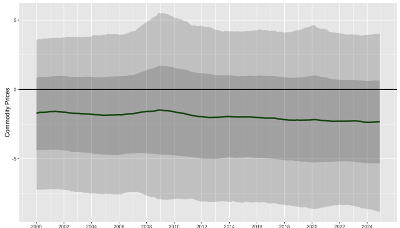
(r) $\varepsilon_i \uparrow \rightarrow ex$



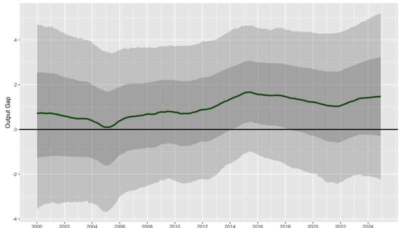
(s) $\varepsilon_i \uparrow \rightarrow i$



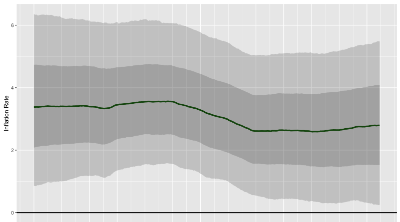
(t) $\varepsilon_i \uparrow \rightarrow \psi$



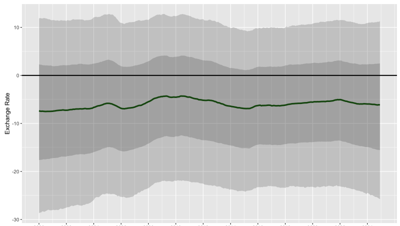
(u) $\varepsilon_\psi \uparrow \rightarrow \hat{y}$



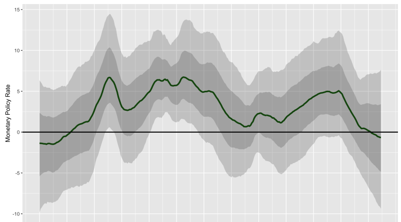
(v) $\varepsilon_\psi \uparrow \rightarrow \pi$



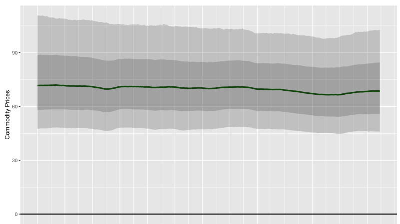
(w) $\varepsilon_\psi \uparrow \rightarrow ex$



(x) $\varepsilon_\psi \uparrow \rightarrow i$



(y) $\varepsilon_\psi \uparrow \rightarrow \psi$

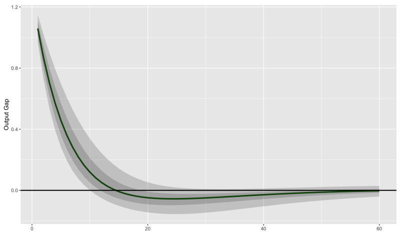


Note: The figure presents the impulse response effects of an output gap shock ($\varepsilon_{\hat{y}}$), inflation rate shock (ε_π), exchange rate shock (ε_{ex}), monetary policy rate shock (ε_i), and commodity price shock (ε_ψ) on the output gap ($\hat{y}$), inflation rate (π), exchange rate (ex), monetary policy rate (i), and commodity prices (ψ) in the baseline model. For each impulse-response pair, the accumulated 18-month impulse responses, highlighting the time-varying nature of the estimates, is displayed, summarizing the IRF estimates across all time points. All panels include the 95% and 68% credible intervals.
Source: Own presentation of data collected from Banco Central do Brasil (2025a), Banco Central do Brasil (2025c), FRED (2025a), FRED (2025c), FRED (2025d), FRED (2025e), and World Bank Group (2025), compiled as indicated in Table 4.1 and processed in accordance with the methodology in Section 5.

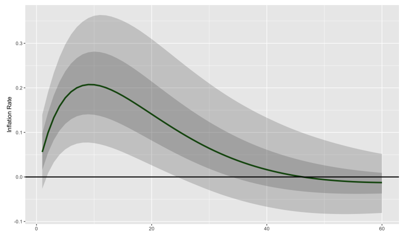
D.2. No Exchange Rate Model

Figure D.3: Time-Invariant IRFs in the Model Excluding Exchange Rate

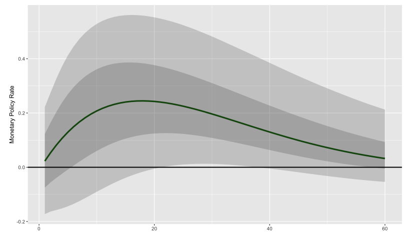
(a) $\varepsilon_{\hat{y}} \uparrow \rightarrow \hat{y}$



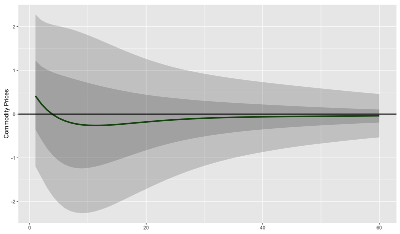
(b) $\varepsilon_{\hat{y}} \uparrow \rightarrow \pi$



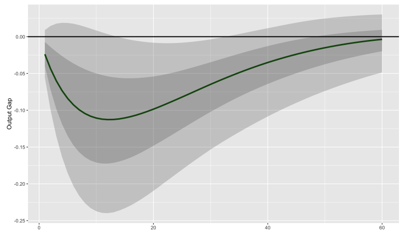
(c) $\varepsilon_{\hat{y}} \uparrow \rightarrow i$



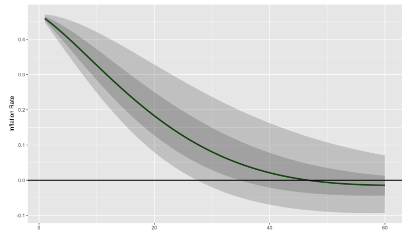
(d) $\varepsilon_{\hat{y}} \uparrow \rightarrow \psi$



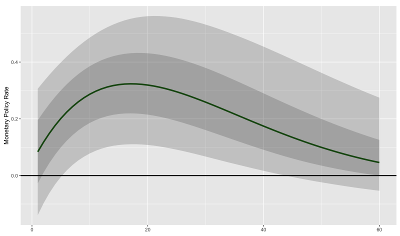
(e) $\varepsilon_{\pi} \uparrow \rightarrow \hat{y}$



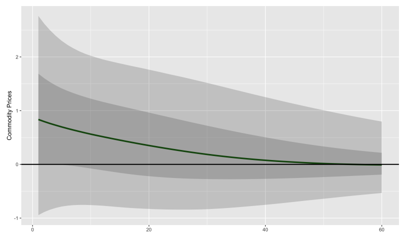
(f) $\varepsilon_{\pi} \uparrow \rightarrow \pi$



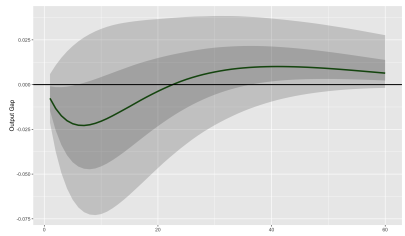
(g) $\varepsilon_{\pi} \uparrow \rightarrow i$



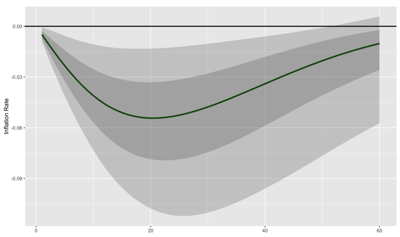
(h) $\varepsilon_{\pi} \uparrow \rightarrow \psi$



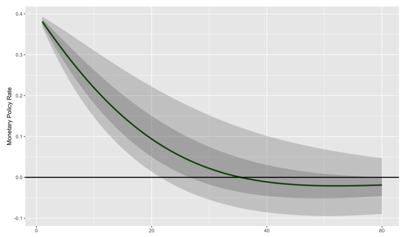
(i) $\varepsilon_{i} \uparrow \rightarrow \hat{y}$



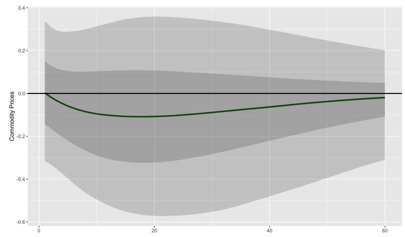
(j) $\varepsilon_{i} \uparrow \rightarrow \pi$



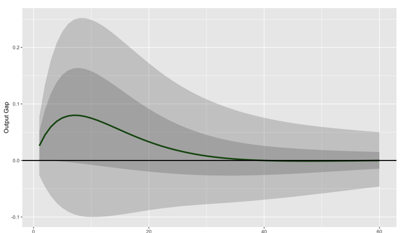
(k) $\varepsilon_{i} \uparrow \rightarrow i$



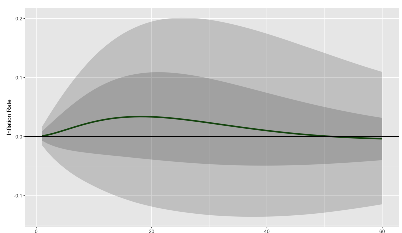
(l) $\varepsilon_{i} \uparrow \rightarrow \psi$



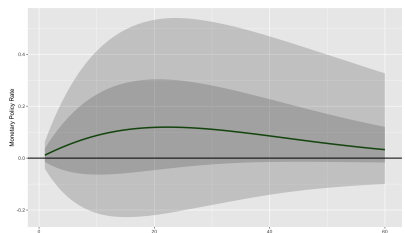
(m) $\varepsilon_{\psi} \uparrow \rightarrow \hat{y}$



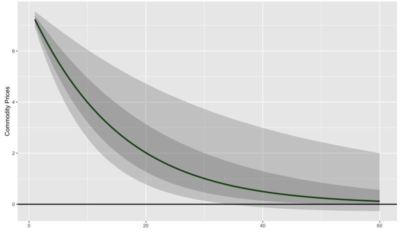
(n) $\varepsilon_{\psi} \uparrow \rightarrow \pi$



(o) $\varepsilon_{\psi} \uparrow \rightarrow i$



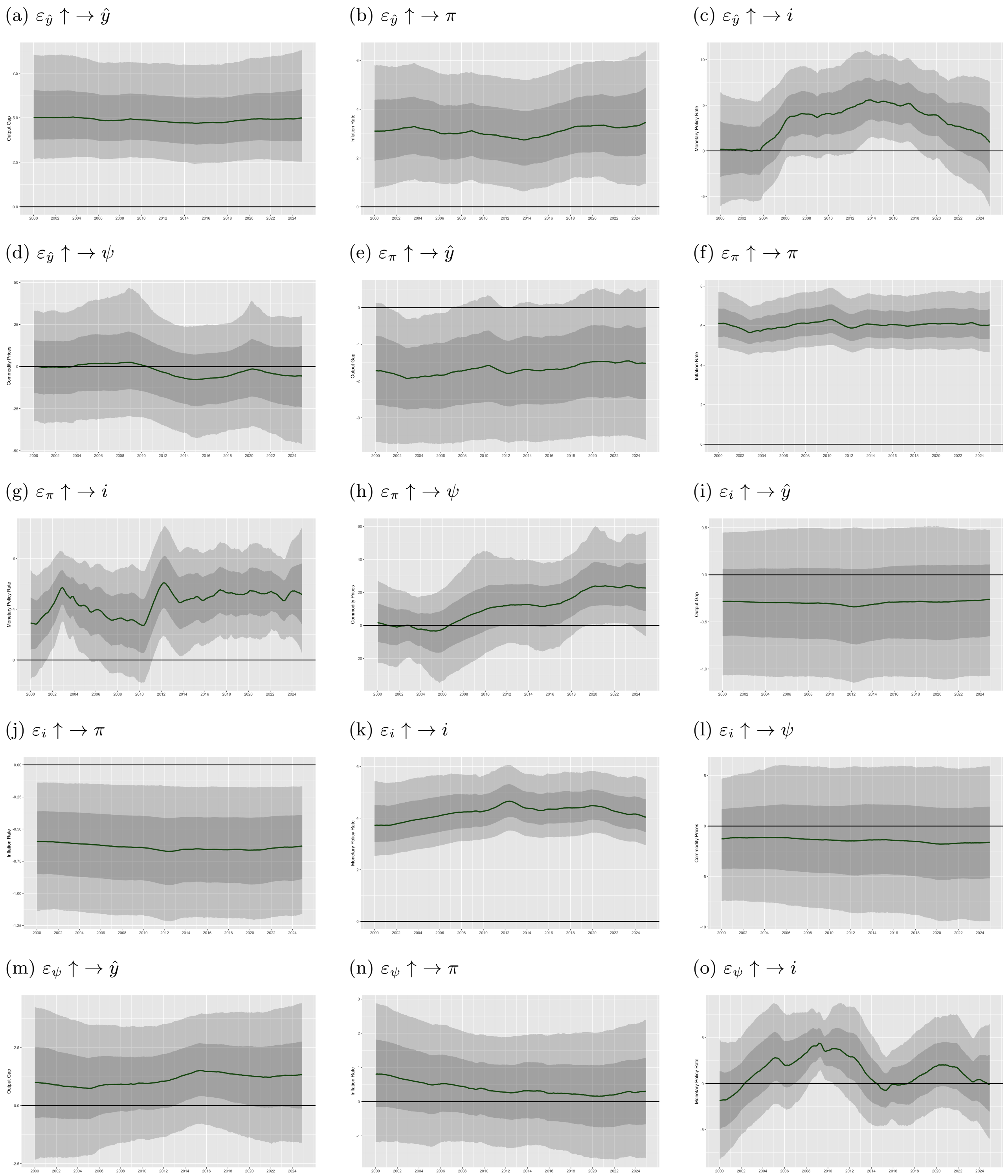
(p) $\varepsilon_\psi \uparrow \rightarrow \psi$



Note: The figure presents the impulse response effects of an output gap shock ($\varepsilon_{\hat{y}}$), inflation rate shock (ε_π), monetary policy rate shock (ε_i), and commodity price shock (ε_ψ) on the output gap ($\hat{y}$), inflation rate (π), monetary policy rate (i), and commodity prices (ψ) in the model excluding exchange rate. For each impulse-response pair, the time-invariant average impulse response over a 60-month horizon is displayed, summarizing the IRF estimates across all time points. All panels include the 95% and 68% credible intervals.

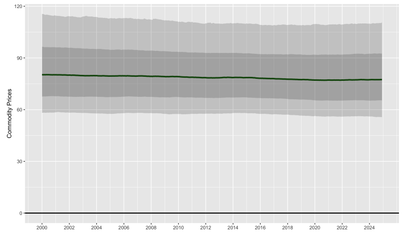
Source: Own presentation of data collected from Banco Central do Brasil (2025a), Banco Central do Brasil (2025c), FRED (2025c), FRED (2025d), FRED (2025e), and World Bank Group (2025), compiled as indicated in Table 4.1 and processed in accordance with the methodology in Section 5.

Figure D.4: Accumulated Time-Varying IRFs in the Model with No Exchange Rate



(a) $\varepsilon_{\hat{y}} \uparrow \rightarrow \hat{y}$
(b) $\varepsilon_{\hat{y}} \uparrow \rightarrow \pi$
(c) $\varepsilon_{\hat{y}} \uparrow \rightarrow i$
(d) $\varepsilon_{\hat{y}} \uparrow \rightarrow \psi$
(e) $\varepsilon_{\pi} \uparrow \rightarrow \hat{y}$
(f) $\varepsilon_{\pi} \uparrow \rightarrow \pi$
(g) $\varepsilon_{\pi} \uparrow \rightarrow i$
(h) $\varepsilon_{\pi} \uparrow \rightarrow \psi$
(i) $\varepsilon_{i} \uparrow \rightarrow \hat{y}$
(j) $\varepsilon_{i} \uparrow \rightarrow \pi$
(k) $\varepsilon_{i} \uparrow \rightarrow i$
(l) $\varepsilon_{i} \uparrow \rightarrow \psi$
(m) $\varepsilon_{\psi} \uparrow \rightarrow \hat{y}$
(n) $\varepsilon_{\psi} \uparrow \rightarrow \pi$
(o) $\varepsilon_{\psi} \uparrow \rightarrow i$

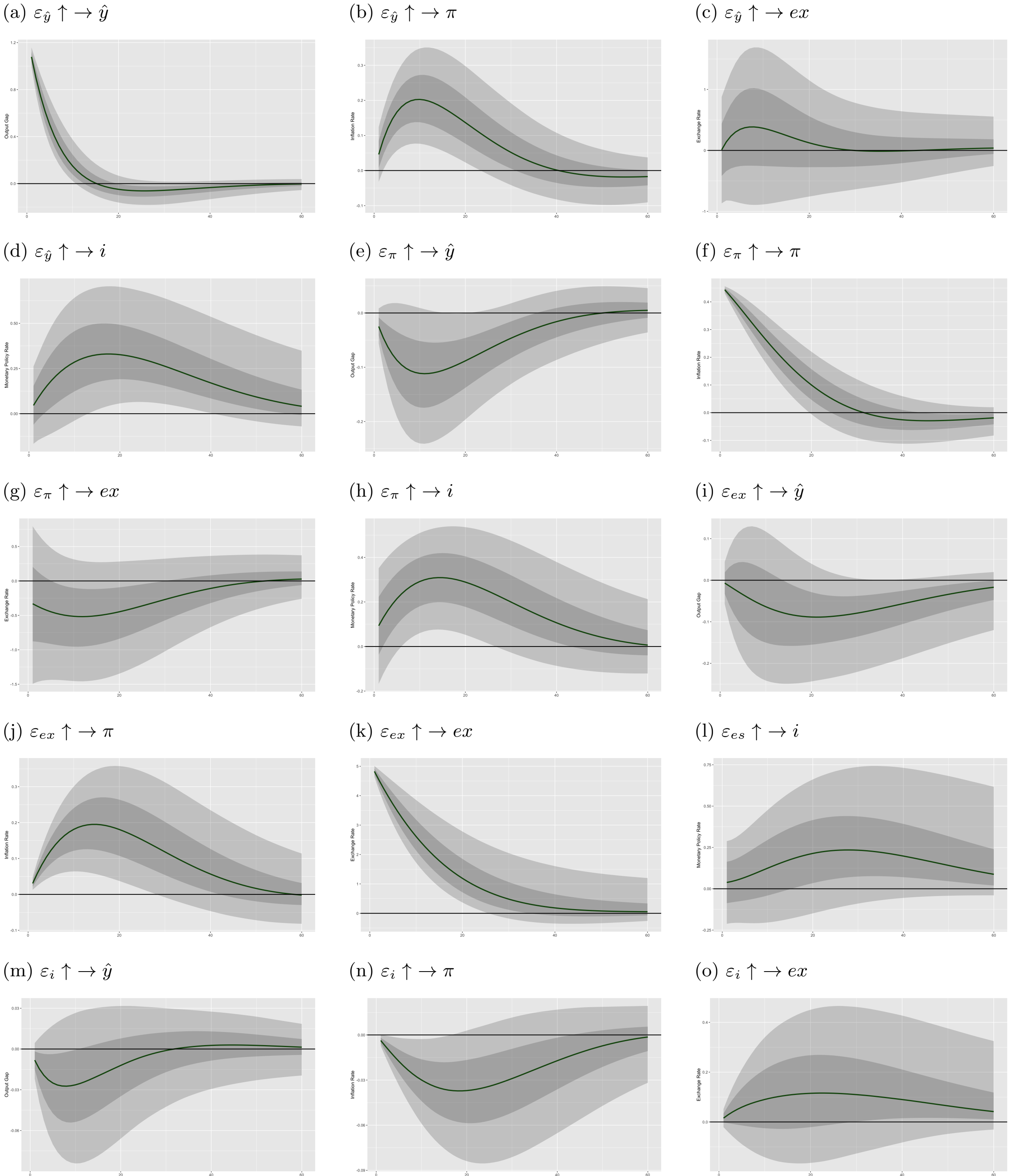
(p) $\varepsilon_\psi \uparrow \rightarrow \psi$



Note: The figure presents the impulse response effects of an output gap shock ($\varepsilon_{\hat{y}}$), inflation rate shock (ε_π), monetary policy rate shock (ε_i), and commodity price shock (ε_ψ) on the output gap ($\hat{y}$), inflation rate (π), monetary policy rate (i), and commodity prices (ψ) in the model excluding exchange rate. For each impulse-response pair, the accumulated 18-month impulse responses, highlighting the time-varying nature of the estimates, is displayed, summarizing the IRF estimates across all time points. All panels include the 95% and 68% credible intervals.
Source: Own presentation of data collected from Banco Central do Brasil (2025a), Banco Central do Brasil (2025c), FRED (2025c), FRED (2025d), FRED (2025e), and World Bank Group (2025), compiled as indicated in Table 4.1 and processed in accordance with the methodology in Section 5.

D.3. No Commodity Price Model

Figure D.5: Time-Invariant IRFs in the Model Excluding Commodity Prices



(a) $\varepsilon_{\hat{y}} \uparrow \rightarrow \hat{y}$ (b) $\varepsilon_{\hat{y}} \uparrow \rightarrow \pi$ (c) $\varepsilon_{\hat{y}} \uparrow \rightarrow ex$

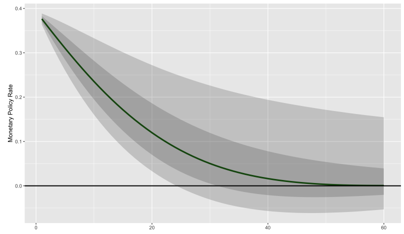
(d) $\varepsilon_{\hat{y}} \uparrow \rightarrow i$ (e) $\varepsilon_{\pi} \uparrow \rightarrow \hat{y}$ (f) $\varepsilon_{\pi} \uparrow \rightarrow \pi$

(g) $\varepsilon_{\pi} \uparrow \rightarrow ex$ (h) $\varepsilon_{\pi} \uparrow \rightarrow i$ (i) $\varepsilon_{ex} \uparrow \rightarrow \hat{y}$

(j) $\varepsilon_{ex} \uparrow \rightarrow \pi$ (k) $\varepsilon_{ex} \uparrow \rightarrow ex$ (l) $\varepsilon_{es} \uparrow \rightarrow i$

(m) $\varepsilon_{i} \uparrow \rightarrow \hat{y}$ (n) $\varepsilon_{i} \uparrow \rightarrow \pi$ (o) $\varepsilon_{i} \uparrow \rightarrow ex$

(p) $\varepsilon_i \uparrow \rightarrow i$

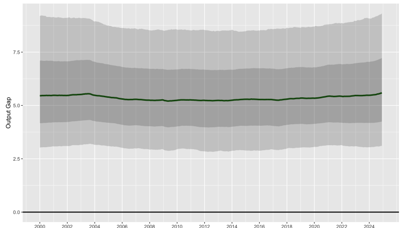


Note: The figure presents the impulse response effects of an output gap shock ($\varepsilon_{\hat{y}}$), inflation rate shock (ε_{π}), exchange rate shock (ε_{ex}), and monetary policy rate shock (ε_i) on the output gap ($\hat{y}$), inflation rate (π), exchange rate (ex), and monetary policy rate (i) in the model excluding commodity prices. For each impulse-response pair, the time-invariant average impulse response over a 60-month horizon is displayed, summarizing the IRF estimates across all time points. All panels include the 95% and 68% credible intervals.

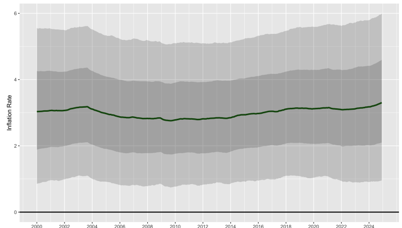
Source: Own presentation of data collected from Banco Central do Brasil (2025a), Banco Central do Brasil (2025c), FRED (2025a), FRED (2025c), and FRED (2025d), compiled as indicated in Table 4.1 and processed in accordance with the methodology in Section 5.

Figure D.6: Accumulated Time-Varying IRFs in the Model with No Commodity Prices

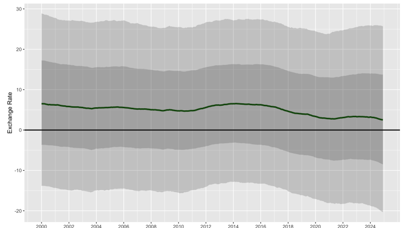
(a) $\varepsilon_{\hat{y}} \uparrow \rightarrow \hat{y}$



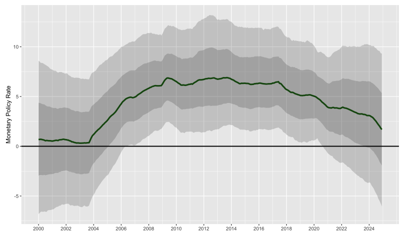
(b) $\varepsilon_{\hat{y}} \uparrow \rightarrow \pi$



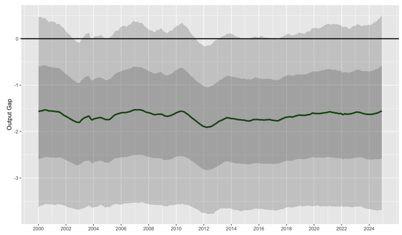
(c) $\varepsilon_{\hat{y}} \uparrow \rightarrow ex$



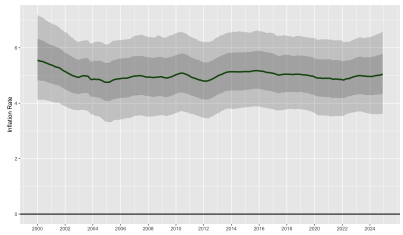
(d) $\varepsilon_{\hat{y}} \uparrow \rightarrow i$



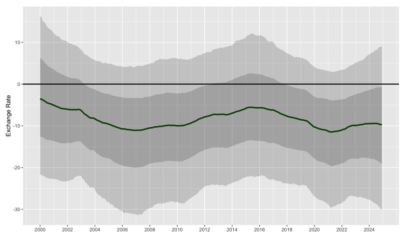
(e) $\varepsilon_{\pi} \uparrow \rightarrow \hat{y}$



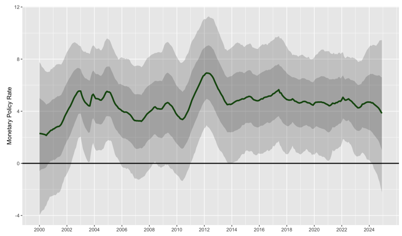
(f) $\varepsilon_{\pi} \uparrow \rightarrow \pi$



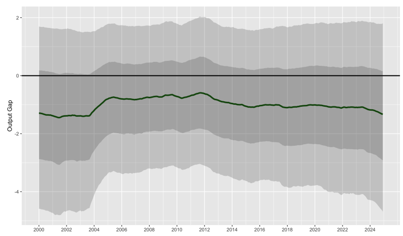
(g) $\varepsilon_{\pi} \uparrow \rightarrow ex$



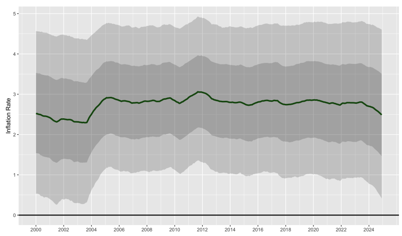
(h) $\varepsilon_{\pi} \uparrow \rightarrow i$



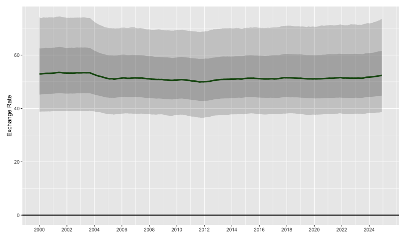
(i) $\varepsilon_{ex} \uparrow \rightarrow \hat{y}$



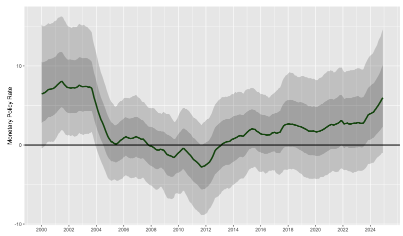
(j) $\varepsilon_{ex} \uparrow \rightarrow \pi$



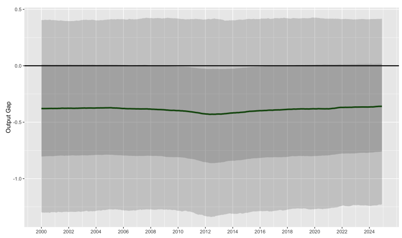
(k) $\varepsilon_{ex} \uparrow \rightarrow ex$



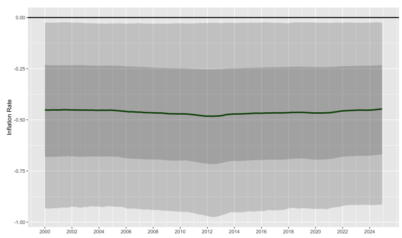
(l) $\varepsilon_{ex} \uparrow \rightarrow i$



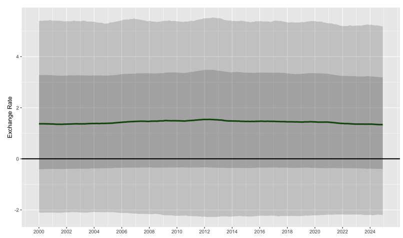
(m) $\varepsilon_{i} \uparrow \rightarrow \hat{y}$



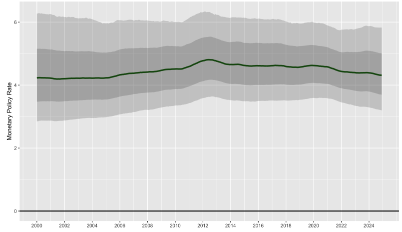
(n) $\varepsilon_{i} \uparrow \rightarrow \pi$



(o) $\varepsilon_{i} \uparrow \rightarrow ex$



(p) $\varepsilon_i \uparrow \rightarrow i$



Note: The figure presents the impulse response effects of an output gap shock ($\varepsilon_{\hat{y}}$), inflation rate shock (ε_{π}), exchange rate shock (ε_{ex}), and monetary policy rate shock (ε_i) on the output gap ($\hat{y}$), inflation rate (π), exchange rate (ex), and monetary policy rate (i) in the model excluding commodity prices. For each impulse-response pair, the accumulated 18-month impulse responses, highlighting the time-varying nature of the estimates, is displayed, summarizing the IRF estimates across all time points. All panels include the 95% and 68% credible intervals.
Source: Own presentation of data collected from Banco Central do Brasil (2025a), Banco Central do Brasil (2025c), FRED (2025a), FRED (2025c), and FRED (2025d), compiled as indicated in Table 4.1 and processed in accordance with the methodology in Section 5.

E. Robustness Analysis

This appendix presents a robustness analysis of the model specifications to assess the stability and reliability of the main empirical findings. The purpose of this analysis is to ensure that the conclusions drawn from the original model specifications are not overly sensitive to specific modelling choices.

Two key robustness checks are implemented. First, the identification strategy is re-evaluated by altering the causal ordering of the variables within the TVP-SVAR-SV framework. This test examines whether the impulse responses and trade-off metrics are robust to alternative assumptions about contemporaneous relationships between variables. Second, the analysis considers an alternative measure for the exchange rate to verify that the observed dynamics are not driven by the specific exchange rate proxy used in the main specification. This addresses potential concerns about measurement bias or oversensitivity to a single bilateral rate.

The results of both robustness checks support the validity of the original findings. While minor quantitative differences are observed, the overall qualitative conclusions remain unchanged, indicating that the results of the original specifications are structurally stable across reasonable variations in model assumptions.

E.1. Alternative New Identification Order

As part of the robustness analysis, an alternative recursive identification scheme is implemented. The new ordering of variables is as follows: commodity prices, monetary policy rate, exchange rate, output gap, and inflation rate. Accordingly, the contemporaneous matrix A_t is specified as:

$$A_t^{\text{New}} \left(\begin{bmatrix} \psi_t \\ i_t \\ ex_t \\ \hat{y}_t \\ \pi_t \end{bmatrix} \right) = \begin{bmatrix} 1 & 0 & 0 & 0 & 0 \\ \alpha_{21,t} & 1 & 0 & 0 & 0 \\ \alpha_{31,t} & \alpha_{32,t} & 1 & 0 & 0 \\ \alpha_{41,t} & \alpha_{42,t} & \alpha_{43,t} & 1 & 0 \\ \alpha_{51,t} & \alpha_{52,t} & \alpha_{53,t} & \alpha_{54,t} & 1 \end{bmatrix} \tag{E.1}$$

This specification mirrors the baseline identification structure with one important exception: the ordering of the output gap and inflation rate has been reversed. In this version, the output gap precedes inflation, such that inflation is ordered last and thus allowed to respond contemporaneously to all other shocks, whereas the output gap is restricted from reacting contemporaneously to inflation shocks.

By implementing this alternative ordering, the robustness of the baseline results is assessed against different but plausible assumptions about the temporal structure of the monetary transmission mechanism. The analysis is structured in three parts. It begins with an evaluation of the model diagnostics to verify convergence and sampling efficiency. This is followed by a comparison of IRFs to those from the original specification. Finally, the impact on the policy trade-off is examined to assess the stability of the main findings.

E.1.1. Diagnostics

Table E.1 presents the Effective Sample Size (ESS) diagnostics for the new identification order. The results are broadly consistent with those from the original model specifications. In both the model excluding the exchange rate and the model excluding commodity prices, the changes in ESS are minimal, with the largest deviation being just 1.39 percentage points.

Notably, the baseline model exhibits a more substantial improvement in the A_t and Σ_t parameter groups, with increases of 12.30 and 12.07 percentage points, respectively. These improvements suggest better chain mixing, reduced autocorrelation, and a more thorough exploration of the parameter space under the new identification scheme - indicating increased overall efficiency in the Bayesian estimation process for the baseline model when the identification order is altered.

Table E.1: Effective Sample Size Results Under Alternative Identification

Model	B_t	A_t	Σ_t	Total
Baseline Model	58.27%	53.03%	44.95%	52.34%
Model Excluding Exchange Rate	61.35%	37.06%	44.21%	51.35%
Model Excluding Commodity Prices	55.70%	54.33%	39.13%	49.19%

Note: The table reports the proportion of effective sample sizes (N_{eff}) falling within the acceptable range of 4,500–5,500 for each parameter group (B_t, A_t, and Σ_t) across the three estimated models with the new identification order. A higher proportion indicates more efficient sampling and lower autocorrelation in the MCMC chains. The "Total" column reflects the overall share of parameters meeting the threshold across all groups. Note that this is not a simple average of the group-level proportions, as each group contains a different number of parameters. In the baseline model, B_t comprises 9,000 parameters, A_t 3,000, and Σ_t 7,500. In the alternative specifications, the corresponding group sizes are 6,000, 1,800, and 4,800 parameters, respectively.
Source: Own presentation of data collected from Banco Central do Brasil (2025a), Banco Central do Brasil (2025c), FRED (2025a), FRED (2025c), FRED (2025d), FRED (2025e), and World Bank Group (2025), compiled as indicated in Table 4.1 and processed in accordance with the methodology in Section 5.

Turning to Geweke's convergence diagnostics, shown in Table E.2, the picture is more mixed. The baseline model and the model excluding the exchange rate both show a decline in the proportion of parameters that meet the convergence criterion - falling by 1.63 and 23.68 percentage points, respectively. In the case of the model excluding the exchange rate, this reduction affects all parameter groups, and may reflect increased sensitivity to the reordering of variables.

In contrast, the model excluding commodity prices shows an improvement in convergence diagnostics, with a 6.06 percentage point increase in the share of parameters satisfying the criterion. This suggests that the new identification ordering improves convergence for this specification, potentially by better aligning the causal structure with the underlying data-generating process.

Table E.2: Geweke's Convergence Diagnostic Results Under Alternative Identification

Model	B_t	A_t	Σ_t	Total
Baseline Model	67.79%	81.03%	81.77%	75.21%
Model Excluding Exchange Rate	58.25%	65.50%	54.67%	57.92%
Model Excluding Commodity Prices	89.95%	86.22%	85.33%	87.66%

Note: The table presents the proportion of parameters in each model group (B_t, A_t, Σ_t) for which Geweke's convergence diagnostic indicates no significant difference between the early and late segments of the Markov chains in the models with the new identification order. A parameter is considered to have passed the Geweke test if its Z-score lies within the 95% confidence interval of a standard normal distribution, i.e., between -1.96 and $+1.96$. Higher proportions indicate greater evidence of convergence to the stationary distribution. The "Total" column reflects the overall share of parameters meeting the threshold across all groups. Note that this is not a simple average of the group-level proportions, as each group contains a different number of parameters. In the baseline model, B_t comprises 9,000 parameters, A_t 3,000, and Σ_t 7,500. In the alternative specifications, the corresponding group sizes are 6,000, 1,800, and 4,800 parameters, respectively.
Source: Own presentation of data collected from Banco Central do Brasil (2025a), Banco Central do Brasil (2025c), FRED (2025a), FRED (2025c), FRED (2025d), FRED (2025e), and World Bank Group (2025), compiled as indicated in Table 4.1 and processed in accordance with the methodology in Section 5.

In summary, the new identification order leads to better ESS diagnostics in the baseline model but has mixed effects on convergence, improving it in one model while worsening it in another.

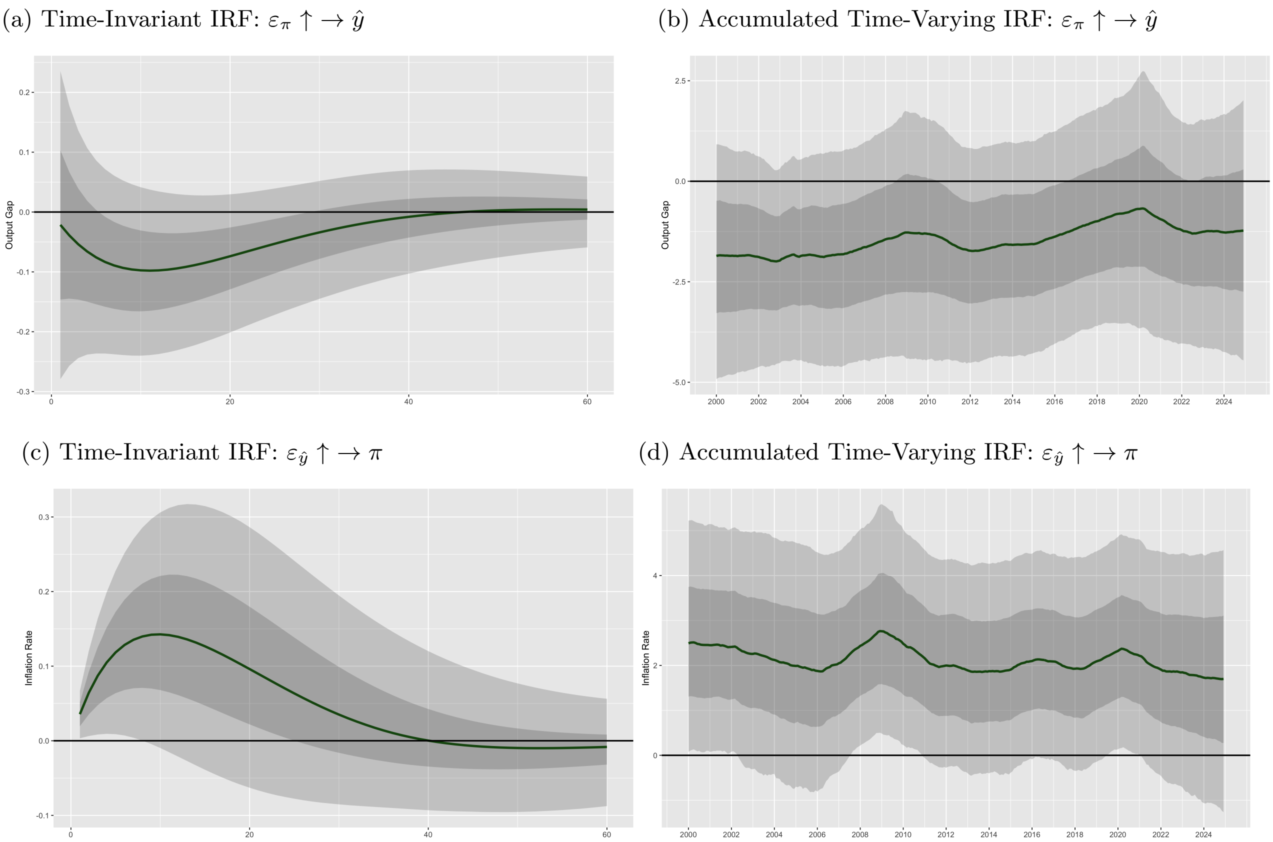
E.1.2. Impulse Response Analysis

This section compares the time-invariant and time-varying IRFs of the model under the new identification order to those from the original specification.

As shown in Figure E.1 and Figure 6.1, the overall dynamics remain consistent across both baseline specifications. Specifically, the effect of an inflation shock on the output gap, and vice versa, displays a similar pattern in both models. One notable difference is that the immediate effects of an inflation shock on the output gap is weaker in the revised model. This is expected, as the inflation rate is now ordered last and therefore does not contemporaneously influence other variables. However, this adjustment has only a marginal impact on the subsequent dynamics. The accumulated 18-month time-varying effect of an inflation shock on the output gap remains nearly unchanged, suggesting that the reordering does not materially alter the medium-term transmission of inflation shocks.

Similarly, the IRF of a shock to the output gap on the inflation rate is virtually unaffected in both magnitude and shape. This indicates that the causal reordering does not compromise the core findings regarding the inflation-output trade-off.

Figure E.1: Trade-Off Between Inflation Rate and Output Gap in the Baseline Model



(a) Time-Invariant IRF: $\varepsilon_{\pi} \uparrow \rightarrow \hat{y}$

(b) Accumulated Time-Varying IRF: $\varepsilon_{\pi} \uparrow \rightarrow \hat{y}$

(c) Time-Invariant IRF: $\varepsilon_{\hat{y}} \uparrow \rightarrow \pi$

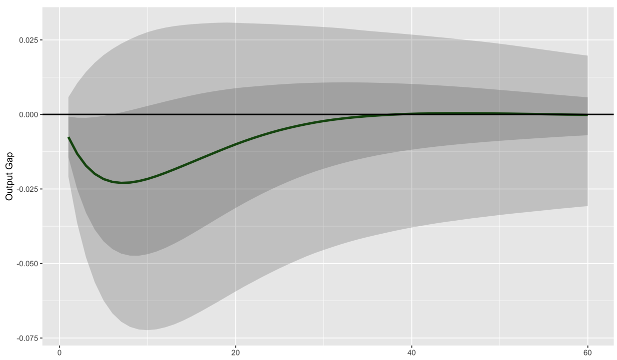
(d) Accumulated Time-Varying IRF: $\varepsilon_{\hat{y}} \uparrow \rightarrow \pi$

Note The figure presents the impulse response effects of an inflation rate shock (ε_{π}) on the output gap ($\hat{y}$) and an output gap shock ($\varepsilon_{\hat{y}}$) on the inflation rate (π) in the baseline model with the new identification order. For each variable, the left-hand panel displays the time-invariant average impulse response over a 60-month horizon, summarizing the IRF estimates across all time points. In contrast, the right-hand panel illustrates the accumulated 18-month impulse responses, highlighting the time-varying nature of the estimates. All panels include the 95% and 68% credible intervals.
Source: Own presentation of data collected from Banco Central do Brasil (2025a), Banco Central do Brasil (2025c), FRED (2025a), FRED (2025c), FRED (2025d), FRED (2025e), and World Bank Group (2025), compiled as indicated in Table 4.1 and processed in accordance with the methodology in Section 5.

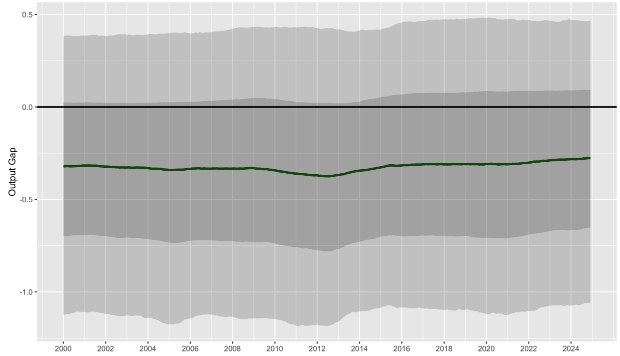
Likewise, a shock to the monetary policy rate yields nearly identical effects on both the output gap and the inflation rate in the revised baseline model, as shown by the comparison of IRF in Figure E.2 and Figure 6.2. Both the timing and magnitude of the responses are virtually indistinguishable between the two specifications. This suggests that the change in the causal ordering has no material effect on how monetary policy shocks propagate through the model. The transmission mechanism from the policy rate to inflation and output remains intact, indicating that the monetary authority's influence on the economy is robust to this reordering assumption.

Figure E.2: A Shock to the Monetary Policy Rate in the Baseline Model

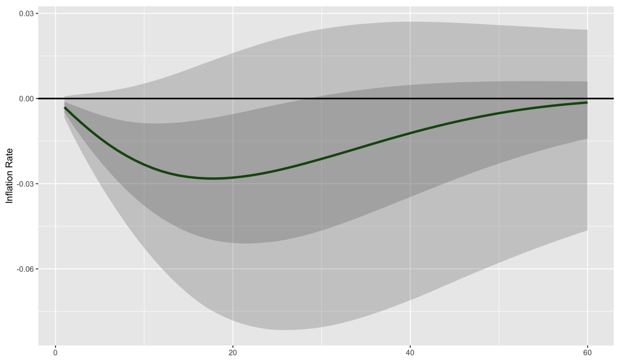
(a) Time-Invariant IRF: $\varepsilon_i \uparrow \rightarrow \hat{y}$



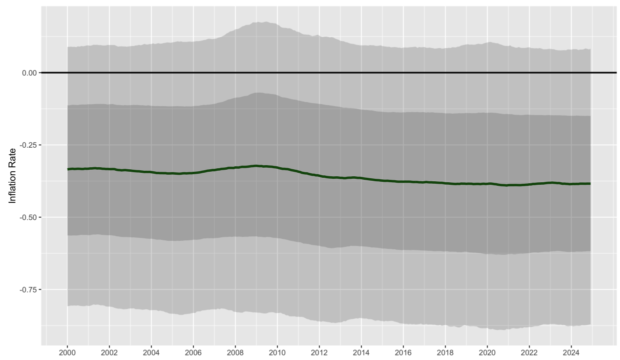
(b) Accumulated Time-Varying IRF: $\varepsilon_i \uparrow \rightarrow \hat{y}$



(c) Time-Invariant IRF: $\varepsilon_i \uparrow \rightarrow \pi$



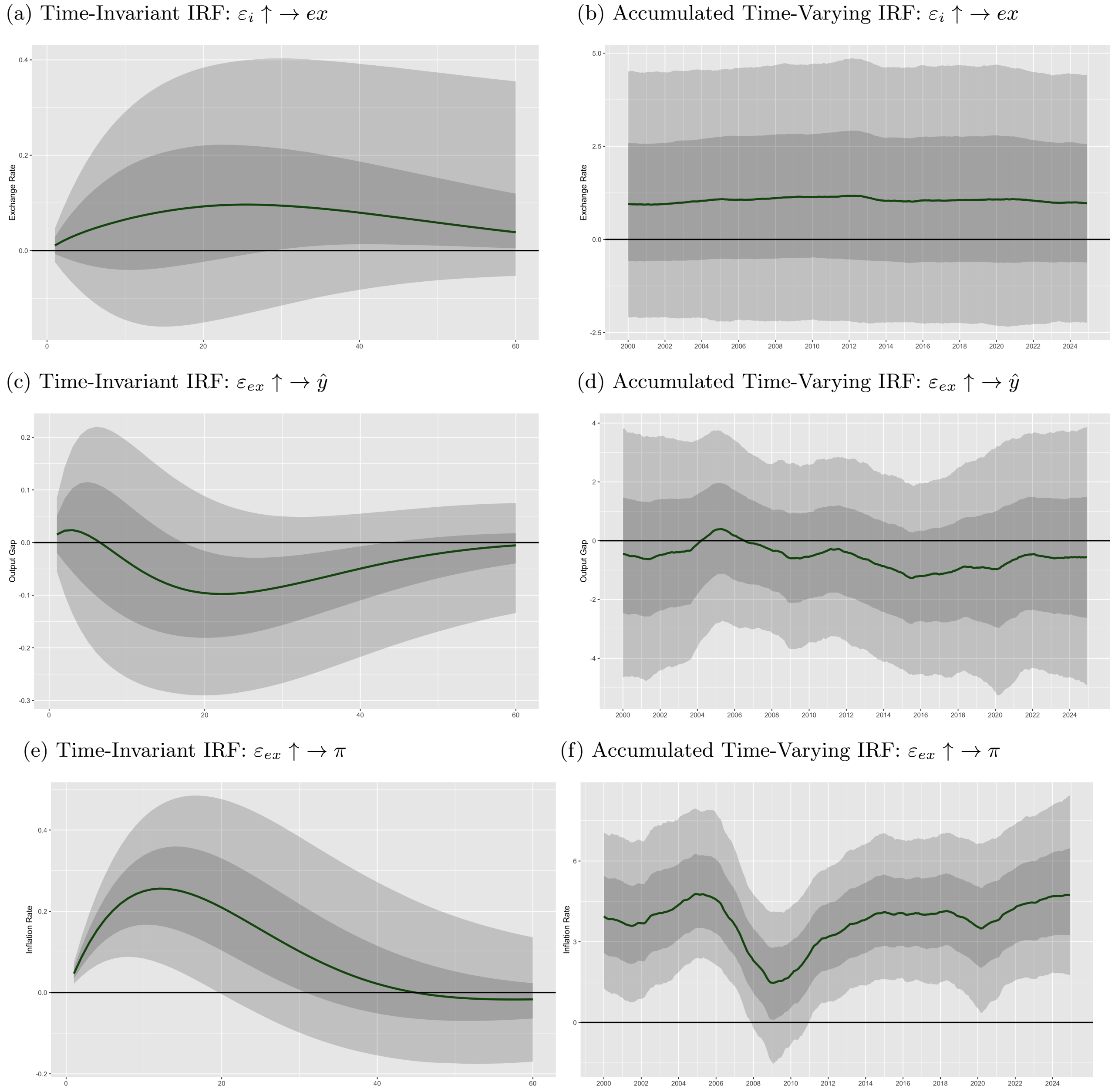
(d) Accumulated Time-Varying IRF: $\varepsilon_i \uparrow \rightarrow \pi$



Note The figure presents the impulse response effects of a monetary policy rate shock (ε_i) on the output gap ($\hat{y}$) and inflation rate (π) response variables in the baseline model with the new identicaiton order. For each variable, the left-hand panel displays the time-invariant average impulse response over a 60-month horizon, summarizing the IRF estimates across all time points. In contrast, the right-hand panel illustrates the accumulated 18-month impulse responses, highlighting the time-varying nature of the estimates. All panels include the 95% and 68% credible intervals.
Source: Own presentation of data collected from Banco Central do Brasil (2025a), Banco Central do Brasil (2025c), FRED (2025a), FRED (2025c), FRED (2025d), FRED (2025e), and World Bank Group (2025), compiled as indicated in Table 4.1 and processed in accordance with the methodology in Section 5.

Turning to the exchange rate channel, the impulse response analysis reveals that the role of the exchange rate remains virtually unchanged across the two baseline specifications. As shown in Figure E.3 and Figure 6.3, the dynamics of the exchange rate in response to monetary policy shocks are highly consistent between the models. In both specifications, the exchange rate reacts similarly to interest rate shocks, indicating that the causal reordering does not alter the transmission of monetary policy through the exchange rate channel. Moreover, the subsequent effects of exchange rate movements on the output gap and inflation rate also exhibit no meaningful differences across the two identification schemes.

Figure E.3: Impulse Responses for the Exchange Rate Channel in the Baseline Model



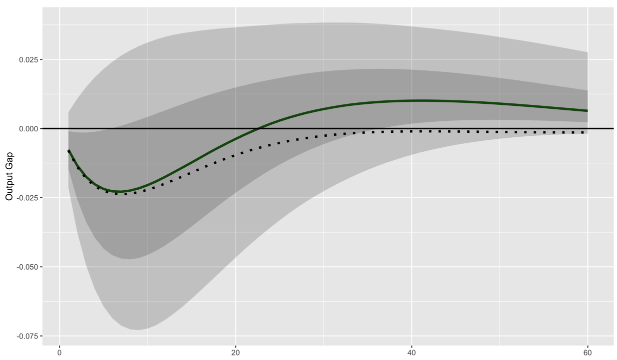
Note The figure presents the impulse response effects of a monetary policy rate shock (ε_i) on the exchange rate (ex) as well an exchange rate shock (ε_{ex}) on the output gap ($\hat{y}$) and inflation rate (π) response variables in the baseline model in the model with the new identification order. For each variable, the left-hand panel displays the time-invariant average impulse response over a 60-month horizon, summarizing the IRF estimates across all time points. In contrast, the right-hand panel illustrates the accumulated 18-month impulse responses, highlighting the time-varying nature of the estimates. All panels include the 95% and 68% credible intervals.

Source: Own presentation of data collected from Banco Central do Brasil (2025a), Banco Central do Brasil (2025c), FRED (2025a), FRED (2025c), FRED (2025d), FRED (2025e), and World Bank Group (2025), compiled as indicated in Table 4.1 and processed in accordance with the methodology in Section 5.

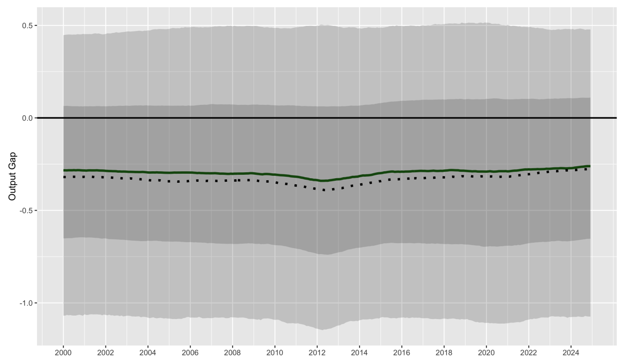
This suggests that the exchange rate's role as an transmission channel is robust to the change in variable ordering, further supporting the structural stability of the model and reinforcing the validity of the original conclusions regarding the impact of exchange rate dynamics on macroeconomic outcomes.

Figure E.4: A Shock to the Monetary Policy Rate in the Model Excluding Exchange Rate

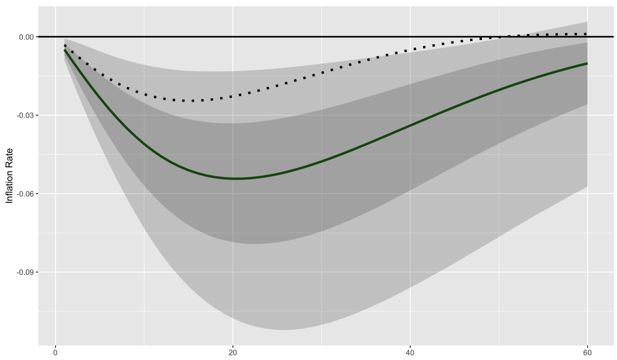
(a) Time-Invariant IRF: $\varepsilon_i \uparrow \rightarrow \hat{y}$



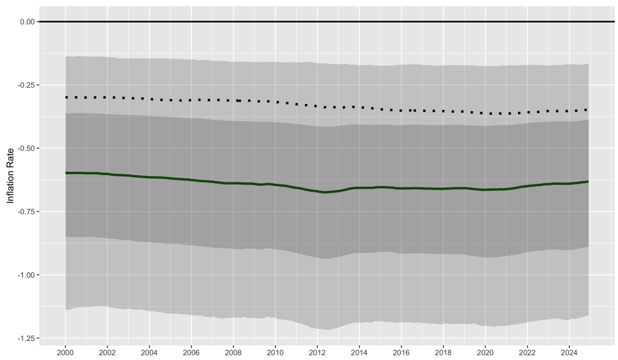
(b) Accumulated Time-Varying IRF: $\varepsilon_i \uparrow \rightarrow \hat{y}$



(c) Time-Invariant IRF: $\varepsilon_i \uparrow \rightarrow \pi$



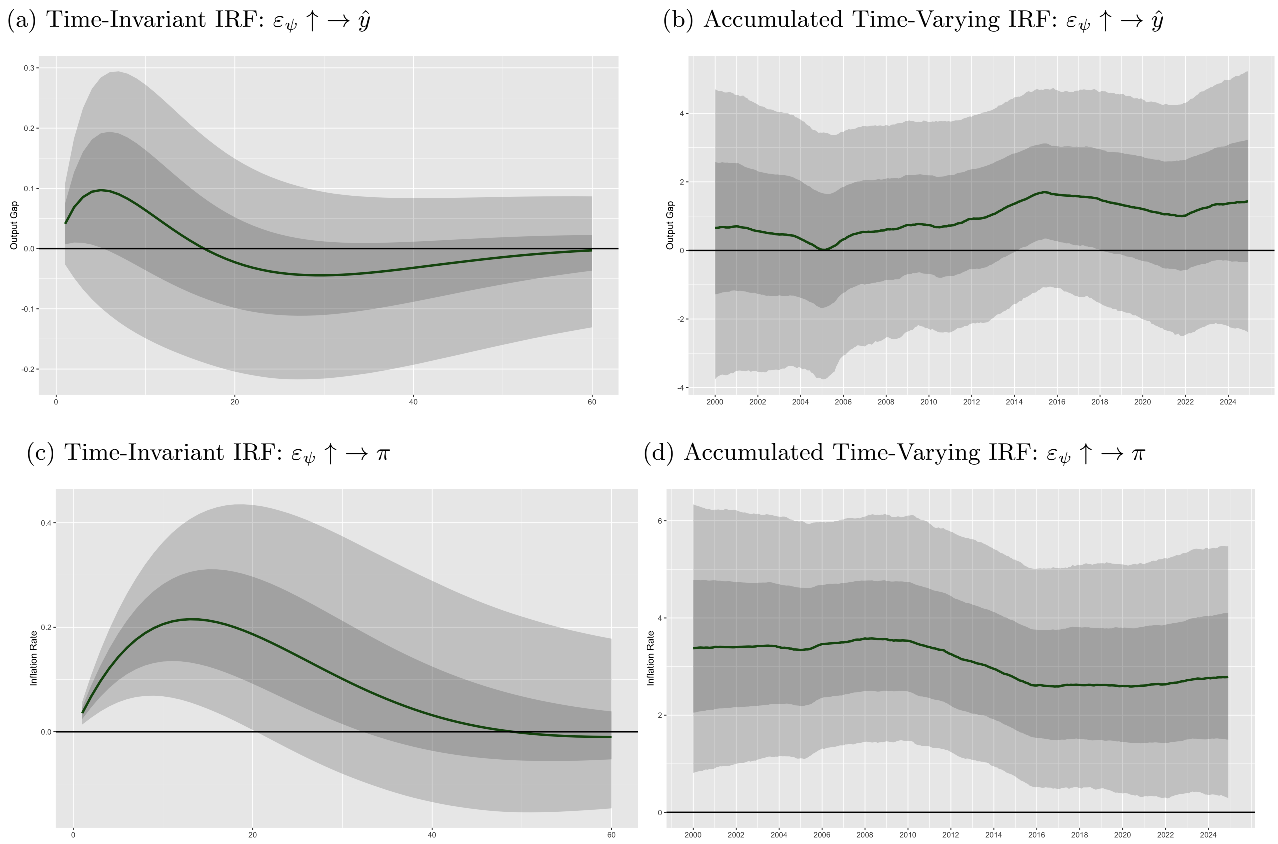
(d) Accumulated Time-Varying IRF: $\varepsilon_i \uparrow \rightarrow \pi$



Note The figure presents the impulse response effects of a monetary policy rate shock (ε_i) on the output gap ($\hat{y}$) and inflation rate (π) response variables in the model with no exchange rate and the new identification order. For each variable, the left-hand panel displays the time-invariant average impulse response over a 60-month horizon, summarizing the IRF estimates across all time points. In contrast, the right-hand panel illustrates the accumulated 18-month impulse responses, highlighting the time-varying nature of the estimates. All panels include the 95% and 68% credible intervals as well as a dotted line for the corresponding impulse-response estimate in the baseline model.
Source: Own presentation of data collected from Banco Central do Brasil (2025a), Banco Central do Brasil (2025c), FRED (2025a), FRED (2025c), FRED (2025d), FRED (2025e), and World Bank Group (2025), compiled as indicated in Table 4.1 and processed in accordance with the methodology in Section 5.

This conclusion is further supported by the comparison of IRFs in the model excluding the exchange rate. Specifically, Figure E.4 and Figure 6.4 illustrate the effects of a monetary policy rate shock on the output gap and inflation rate under the two identification schemes. The results show that the dynamic responses are nearly identical across the specifications. Both the magnitude and timing of the effects remain consistent, indicating that the exclusion of the exchange rate variable does not interact significantly with the change in causal ordering. This further supports the view that the model's core transmission dynamics - particularly the relationship between monetary policy, inflation, and output - are robust to the identification assumptions.

Figure E.5: Impulse Responses for the Commodity Prices Channel in the Baseline Model



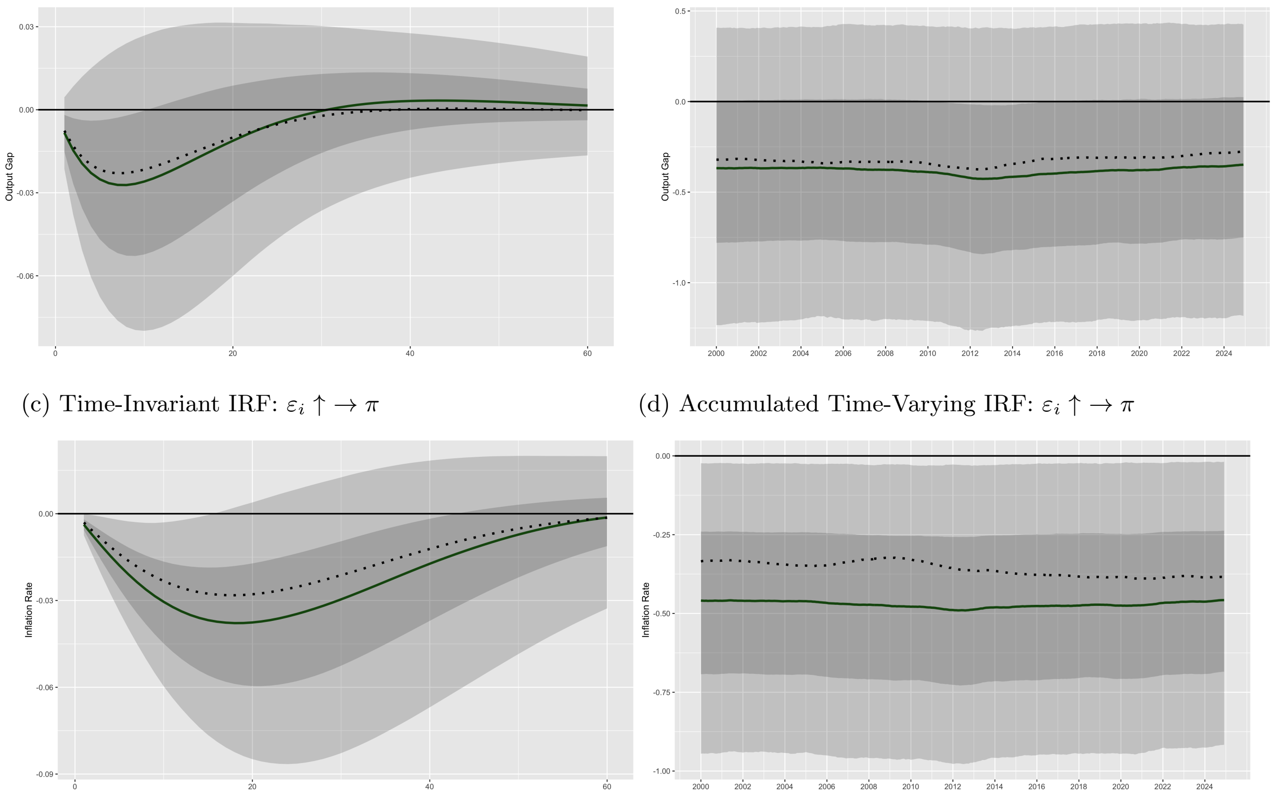
Note The figure presents the impulse response effects of a monetary policy rate shock (ε_i) on the commodity prices (ψ) as well a commodity price shock (ε_ψ) on the output gap ($\hat{y}$) and inflation rate (π) response variables in the baseline model with the new identification order. For each variable, the left-hand panel displays the time-invariant average impulse response over a 60-month horizon, summarizing the IRF estimates across all time points. In contrast, the right-hand panel illustrates the accumulated 18-month impulse responses, highlighting the time-varying nature of the estimates. All panels include the 95% and 68% credible intervals.
Source: Own presentation of data collected from Banco Central do Brasil (2025a), Banco Central do Brasil (2025c), FRED (2025a), FRED (2025c), FRED (2025d), FRED (2025e), and World Bank Group (2025), compiled as indicated in Table 4.1 and processed in accordance with the methodology in Section 5.

Examining the effects of the commodity price channel in the baseline specifications, as shown in Figure E.5 and Figure 6.5, reveals no meaningful differences between the two identification schemes. The impact of commodity price fluctuations on the output gap and inflation rate appears unchanged. This consistency suggests that the role of the commodity price channel in the monetary transmission mechanism is robust to the reordering of variables. The channel behaves similarly in both model specifications, reinforcing the conclusion that the baseline findings are not sensitive to this particular identification assumption.

Figure E.6: A Shock to the Monetary Policy Rate in the Model Excluding Commodity Prices

(a) Time-Invariant IRF: $\varepsilon_i \uparrow \rightarrow \hat{y}$ (b) Accumulated Time-Varying IRF: $\varepsilon_i \uparrow \rightarrow \hat{y}$

(c) Time-Invariant IRF: $\varepsilon_i \uparrow \rightarrow \pi$ (d) Accumulated Time-Varying IRF: $\varepsilon_i \uparrow \rightarrow \pi$



Note The figure presents the impulse response effects of a monetary policy rate shock (ε_i) on the output gap ($\hat{y}$) and inflation rate (π) response variables in the model with no commodity prices and the new identification order. For each variable, the left-hand panel displays the time-invariant average impulse response over a 60-month horizon, summarizing the IRF estimates across all time points. In contrast, the right-hand panel illustrates the accumulated 18-month impulse responses, highlighting the time-varying nature of the estimates. All panels include the 95% and 68% credible intervals as well as a dotted line for the corresponding impulse-response estimate in the baseline model.
Source: Own presentation of data collected from Banco Central do Brasil (2025a), Banco Central do Brasil (2025c), FRED (2025a), FRED (2025c), FRED (2025d), FRED (2025e), and World Bank Group (2025), compiled as indicated in Table 4.1 and processed in accordance with the methodology in Section 5.

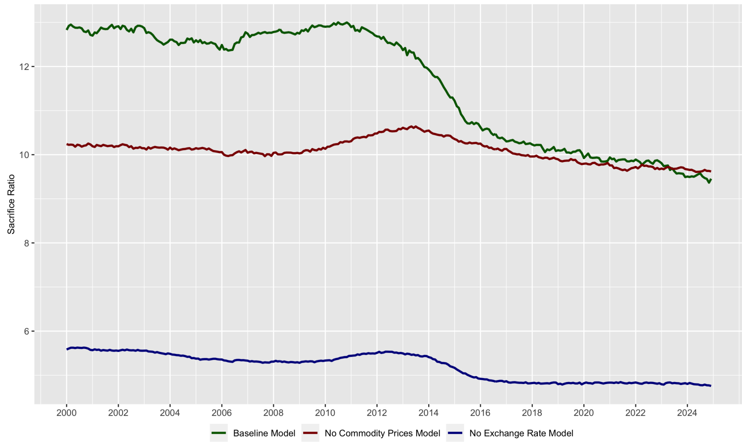
Similarly, the exclusion of commodity prices does not appear to alter the transmission of monetary policy. As shown in Figure E.6 and Figure 6.6, the impulse responses of the output gap and inflation rate to a monetary policy rate shock are nearly identical across the two specifications. Both the magnitude and timing of the responses remain consistent, indicating that the core dynamics of monetary policy transmission are unaffected by the causal reordering, even when the commodity price channel is excluded. This further confirms the robustness of the model's structural relationships under varying identification assumptions.

E.1.3. Policy Trade-Off Analysis

This section evaluates whether the economic trade-off results, measured by the evolution of the sacrifice ratio, are sensitive to the revised identification scheme. Specifically, it compares the outcomes from the model with the new variable ordering to those obtained under the original specification, in order to assess the robustness of the conclusions regarding Brazil's inflation-output trade-off.

As shown in Figure E.7, the estimated sacrifice ratios under the new identification are largely consistent with those from the original specification, presented in Figure 7.2. The level effects are nearly identical in the baseline model, while the models excluding the exchange rate and commodity price channels exhibit slightly lower initial sacrifice ratios under the new ordering. The time dynamics of the sacrifice ratios are also broadly similar across the two specifications. In both, the baseline model exhibits the highest sacrifice ratio at the start of the sample period. In the new identification, there is a slight decline in the early years, followed by a return to the initial level - whereas the original specification shows a more stable trajectory during that period.

Figure E.7: Sacrifice Ratio for All Model Specifications, 2000M1-2024M12



Note: The figure displays the monthly evolution of the sacrifice ratio from January 2000 to December 2024 across three TVP-SVAR-SV model specifications: the baseline model (green), the model excluding the exchange rate variable (blue), and the model excluding commodity prices (red). All model are with the new identification order. In each case, the sacrifice ratio is computed as the cumulative response of the output gap relative to the level response of inflation 18 months after a monetary policy rate shock. Comparing the trajectories allows for an assessment of the exchange rate and commodity prices transmission channels alter the trade-off between disinflation and output loss.
Source: Own presentation of data collected from Banco Central do Brasil (2025a), Banco Central do Brasil (2025c), FRED (2025a), FRED (2025c), FRED (2025d), FRED (2025e), and World Bank Group (2025), compiled as indicated in Table 4.1 and processed in accordance with the methodology in Section 5.

From around 2012 onwards, both versions of the baseline model begin to show a declining trend in the sacrifice ratio, indicating improved monetary policy efficiency. Notably, the original specification of the baseline model reaches a more favourable trade-off relative to the model without the commodity price channel by around 2016, whereas this same point is reached later, around 2022, under the new identification. However, this delay must be interpreted in light of the fact that the model excluding the commodity price channel begins at a lower level in the new specification.

In both model specifications, the version excluding the exchange rate channel consistently yields the lowest sacrifice ratio across the entire period. This finding reinforces the conclusion from earlier analyses: the exchange rate channel tends to amplify output costs in response to disinflationary policy.

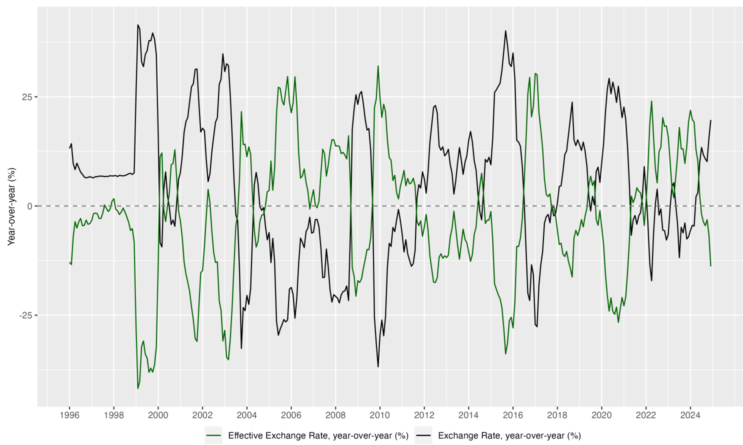
Overall, the use of an alternative identification scheme does not materially alter the results of the economic trade-off analysis. The key patterns and relative comparisons remain intact, supporting the robustness of the original conclusions regarding Brazil's evolving inflation-output trade-off.

E.2. Alternative Exchange Rate Measure

This section examines whether the main results are sensitive to the specific exchange rate measure used. In the original model specifications, the exchange rate is represented by the year-over-year percentage change in BRL/USD nominal rate. To test the robustness of the findings, this variable is replaced with the year-over-year percentage change in the Broad Effective Exchange Rate for Brazil, sourced from FRED (2025b).

In Figure E.8, the original measure of the of the exchange rate is illustrated along with the alternative measure for the exchange rate.

Figure E.8: Exchange Rate Measures for Brazil, 1996M1-2024M12



Note: The figure displays the evolution of two exchange rate measures for Brazil from January 1996 to December 2024. The black series shows the bilateral nominal exchange rate between the BRL and USD, where an increase indicates a depreciation of the BRL. The green series is the Broad Effective Exchange Rate, which captures Brazil's currency value relative to a trade-weighted basket of major trading partners, adjusted for inflation differentials. In this measure, an increase reflects an appreciation of the BRL.
Source: Own illustration of data collected from FRED (2025a) and FRED (2025b).

A key distinction between the two measures lies in their interpretation. The BRL/USD variable was constructed such that an increase signalled a depreciation of the BRL. In contrast, the effective exchange rate is defined such that an increase reflects an appreciation of the domestic currency. This directional difference must be accounted for when interpreting the impulse responses and trade-off dynamics.

The analysis proceeds in three steps. First, the diagnostic results for the revised model are presented to ensure convergence and sampling quality. Second, the robustness of the impulse responses is assessed relative to the original specification. Third, the effect on policy trade-off measures given by the sacrifice ratio is presented.

E.2.1. Diagnostics

Table E.3 presents the ESS diagnostics for the models estimated using the Broad Effective Exchange Rate as an alternative to the BRL/USD rate. Overall, the results are highly consistent with those from the original specification, suggesting stable sampling behaviour and efficient MCMC performance under the revised exchange rate measure. In the baseline model, the total proportion of parameters falling within the acceptable ESS range is 51.01%, which represents a moderate improvement of 6.64 percentage points compared to the original specification. This increase is driven primarily by gains in the B_t and A_t parameter groups, which improve by 7.06 and 12.33 percentage points, respectively. The Σ_t group improves slightly, by 1.46 percentage points. These gains suggest better chain mixing and reduced autocorrelation in the baseline model when using the effective exchange rate.

Table E.3: Effective Sample Size Results Under Alternative Exchange Rate

Model	B_t	A_t	Σ_t	Total
Baseline Model	52.24%	51.47%	49.33%	51.01%
Model Excluding Exchange Rate	75.35%	36.28%	32.25%	53.35%
Model Excluding Commodity Prices	54.40%	59.83%	44.96%	51.58%

Note: The table reports the proportion of effective sample sizes (N_{eff}) falling within the acceptable range of 4,500–5,500 for each parameter group (B_t, A_t, and Σ_t) across the three estimated models with the new exchange rate variable. A higher proportion indicates more efficient sampling and lower autocorrelation in the MCMC chains. The "Total" column reflects the overall share of parameters meeting the threshold across all groups. Note that this is not a simple average of the group-level proportions, as each group contains a different number of parameters. In the baseline model, B_t comprises 9,000 parameters, A_t 3,000, and Σ_t 7,500. In the alternative specifications, the corresponding group sizes are 6,000, 1,800, and 4,800 parameters, respectively.
Source: Own presentation of data collected from Banco Central do Brasil (2025a), Banco Central do Brasil (2025c), FRED (2025b), FRED (2025c), FRED (2025d), FRED (2025e), and World Bank Group (2025), compiled as indicated in Table 4.1 and processed in accordance with the methodology in Section 5.

For the model excluding the exchange rate, the ESS diagnostics are identical between the original specification and the specification with the new exchange rate measure given that the exchange rate is excluded in both models. The model excluding commodity prices shows a minor change in ESS diagnostics. The total ESS proportion is 51.58%, just 0.23 percentage points higher than in the original model.

Taken together, these results suggest that the effective exchange rate variable is a viable alternative to the BRL/USD measure in terms of sampling efficiency. The baseline model benefits modestly from the change, while the alternative specifications show effectively unchanged diagnostics. All models demonstrate acceptable ESS levels, indicating that the MCMC chains are well-behaved and that the parameter spaces have been sufficiently explored under the new exchange rate specification.

Geweke's convergence diagnostic results for the models estimated using the effective exchange rate are reported in Table E.4. The results are largely consistent with those from the original specification in Table 5.2, suggesting that the Markov chains have converged satisfactorily under the revised exchange rate measure.

In the baseline model, 77.15% of the parameters fall within the acceptable Z-score range, indicating no significance difference between the early and late portions of the chains. This represents a small improvement of 0.31 percentage points compared to the original specification. Meanwhile, for the model excluding the exchange rate, convergence diagnostics remain unchanged across all groups due to the exchange rate being excluded in both models.

Table E.4: Geweke's Convergence Diagnostic Results Under Alternative Exchange Rate

Model	B_t	A_t	Σ_t	Total
Baseline Model	72.10%	87.43%	79.11%	77.15%
Model Excluding Exchange Rate	80.35%	85.83%	80.94%	81.60%
Model Excluding Commodity Prices	79.85%	82.83%	79.50%	80.14%

Note: The table presents the proportion of parameters in each model group (B_t, A_t, Σ_t) for which Geweke's convergence diagnostic indicates no significant difference between the early and late segments of the Markov chains in the models with the new exchange rate variable. A parameter is considered to have passed the Geweke test if its Z-score lies within the 95% confidence interval of a standard normal distribution, i.e., between -1.96 and $+1.96$. Higher proportions indicate greater evidence of convergence to the stationary distribution. The "Total" column reflects the overall share of parameters meeting the threshold across all groups. Note that this is not a simple average of the group-level proportions, as each group contains a different number of parameters. In the baseline model, B_t comprises 9,000 parameters, A_t 3,000, and Σ_t 7,500. In the alternative specifications, the corresponding group sizes are 6,000, 1,800, and 4,800 parameters, respectively.
Source: Own presentation of data collected from Banco Central do Brasil (2025a), Banco Central do Brasil (2025c), FRED (2025b), FRED (2025c), FRED (2025d), FRED (2025e), and World Bank Group (2025), compiled as indicated in Table 4.1 and processed in accordance with the methodology in Section 5.

The model excluding commodity prices shows a slight decline in convergence quality under the new specification, with the total proportion of parameters passing the diagnostic decreasing from 81.60% to 80.14%. The most notable reductions occur in the A_t and Σ_t groups, which drop by 10.89 and 8.67 percentage points, respectively. However, the B_t group improves by 7.15 percentage points, partially offsetting the losses.

Overall, the Geweke's convergence diagnostics indicate that all three models exhibit stable and acceptable convergence under the alternative exchange rate measure.

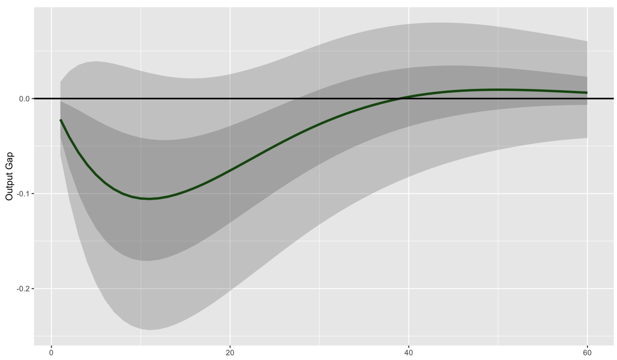
E.2.2. Impulse Response Analysis

To assess the robustness of the transmission dynamics, this section compares IRFs from the baseline model using the alternative exchange rate measure to those from the original specification.

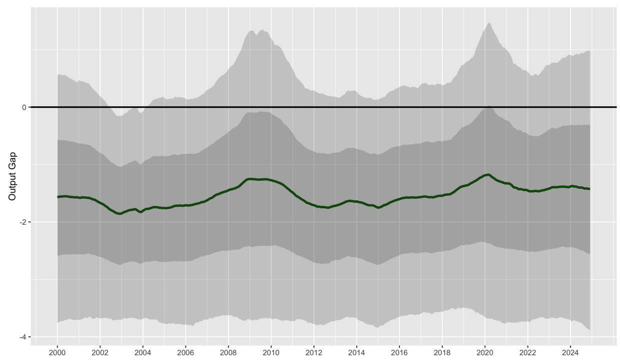
As shown in Figure E.9 and Figure 6.1, the overall dynamics of the inflation-output gap trade-off remain highly consistent across both versions of the baseline model. In particular, the effect of an inflation shock on the output gap and vice versa, follows a nearly identical pattern in both specifications, indicating that the core inflation-output relationship is not sensitive to the choice of exchange rate measure.

Figure E.9: Trade-Off Between Inflation Rate and Output Gap in the Baseline Model

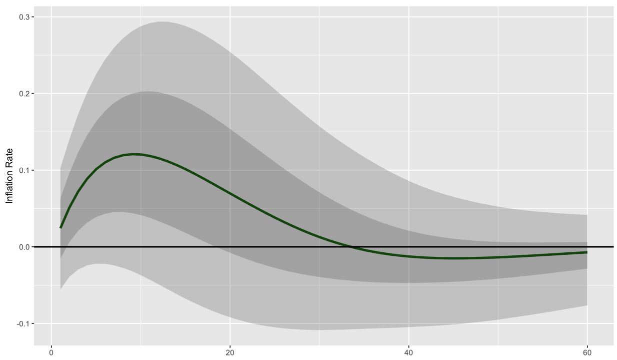
(a) Time-Invariant IRF: $\varepsilon_\pi \uparrow \rightarrow \hat{y}$



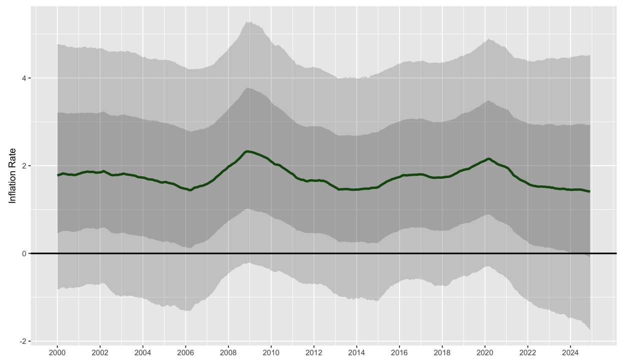
(b) Accumulated Time-Varying IRF: $\varepsilon_\pi \uparrow \rightarrow \hat{y}$



(c) Time-Invariant IRF: $\varepsilon_{\hat{y}} \uparrow \rightarrow \pi$



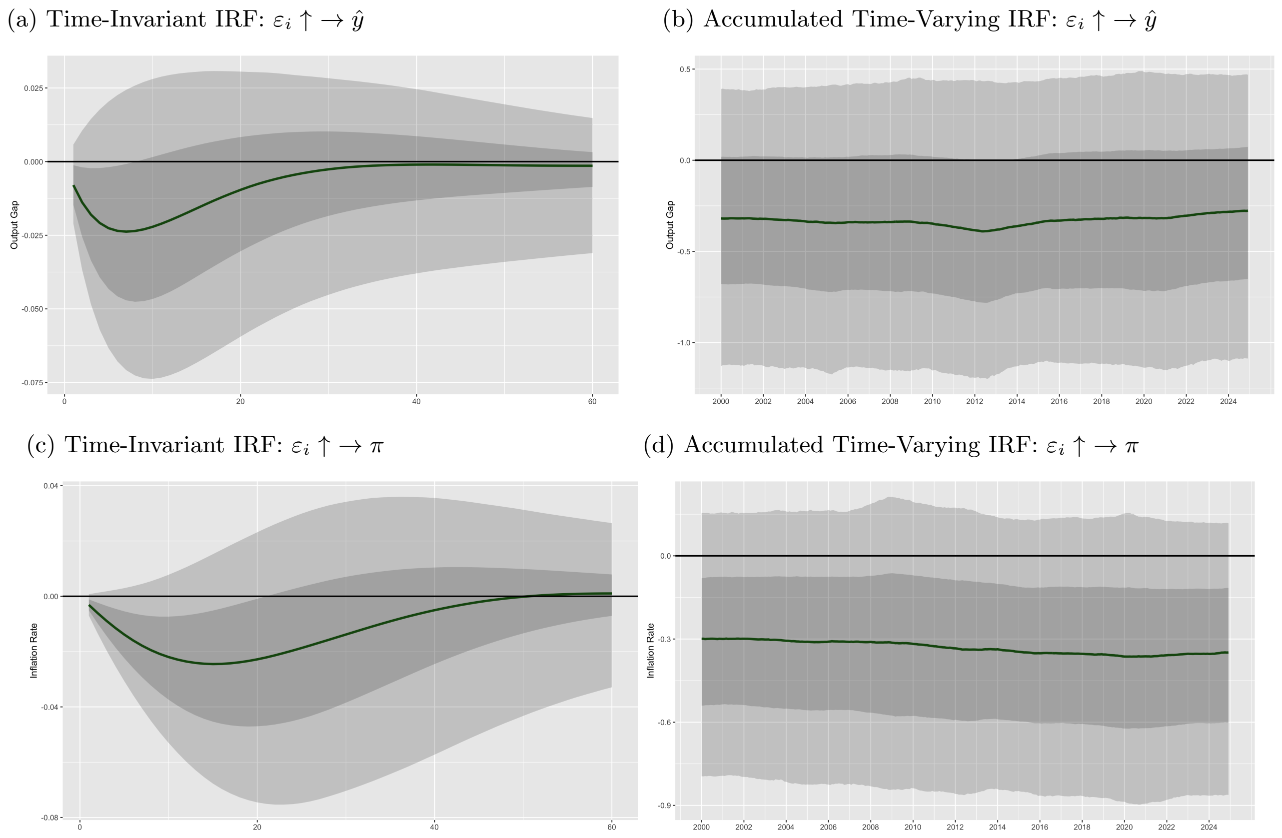
(d) Accumulated Time-Varying IRF: $\varepsilon_{\hat{y}} \uparrow \rightarrow \pi$



Note The figure presents the impulse response effects of an inflation rate shock (ε_π) on the output gap ($\hat{y}$) and an output gap shock ($\varepsilon_{\hat{y}}$) on the inflation rate (π) in the baseline model with effective exchange rate. For each variable, the left-hand panel displays the time-invariant average impulse response over a 60-month horizon, summarizing the IRF estimates across all time points. In contrast, the right-hand panel illustrates the accumulated 18-month impulse responses, highlighting the time-varying nature of the estimates. All panels include the 95% and 68% credible intervals.
Source: Own presentation of data collected from Banco Central do Brasil (2025a), Banco Central do Brasil (2025c), FRED (2025b), FRED (2025c), FRED (2025d), FRED (2025e), and World Bank Group (2025), compiled as indicated in Table 4.1 and processed in accordance with the methodology in Section 5.

Similarly, the impact of a monetary policy rate shock on both the output gap and the inflation rate remains virtually unchanged when the effective exchange rate replaces the BRL/USD measure. As illustrated in Figure E.10 and Figure 6.2, the shape, timing, and intensity of the responses are nearly identical across the two baseline specifications. This consistency indicates that altering the exchange rate variable does not significantly influence the propagation of monetary policy shocks. The fundamental transmission channel from the interest rate to real activity and price dynamics is preserved, highlighting the robustness of the model's structural relationships to this specification change.

Figure E.10: A Shock to the Monetary Policy Rate in the Baseline Model



(a) Time-Invariant IRF: $\varepsilon_i \uparrow \rightarrow \hat{y}$

(b) Accumulated Time-Varying IRF: $\varepsilon_i \uparrow \rightarrow \hat{y}$

(c) Time-Invariant IRF: $\varepsilon_i \uparrow \rightarrow \pi$

(d) Accumulated Time-Varying IRF: $\varepsilon_i \uparrow \rightarrow \pi$

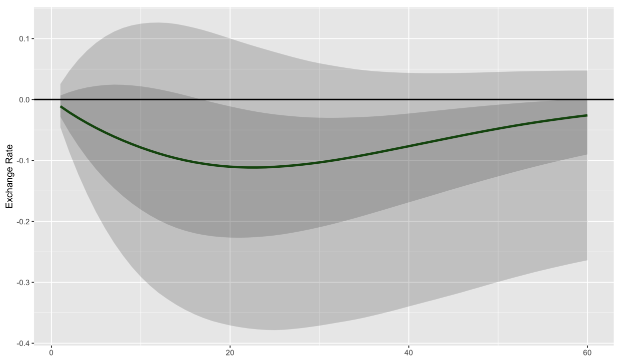
Note The figure presents the impulse response effects of a monetary policy rate shock (ε_i) on the output gap ($\hat{y}$) and inflation rate (π) response variables in the baseline model with effective exchange rate. For each variable, the left-hand panel displays the time-invariant average impulse response over a 60-month horizon, summarizing the IRF estimates across all time points. In contrast, the right-hand panel illustrates the accumulated 18-month impulse responses, highlighting the time-varying nature of the estimates. All panels include the 95% and 68% credible intervals.
Source: Own presentation of data collected from Banco Central do Brasil (2025a), Banco Central do Brasil (2025c), FRED (2025b), FRED (2025c), FRED (2025d), FRED (2025e), and World Bank Group (2025), compiled as indicated in Table 4.1 and processed in accordance with the methodology in Section 5.

Examining the exchange rate channel, the impulse response analysis shows that its role remains fundamentally unchanged across the two baseline specifications. As illustrated in Figure E.11 and Figure 6.3, the response of the exchange rate to a monetary policy shock is consistent in both models. In the original specification, a policy rate increase leads to a depreciation of the BRL, reflected as a positive response in the BRL/USD rate. In contrast, the model using the effective exchange rate shows a positive response following a rate hike. However, due to the inverse sign convention, this corresponds to an appreciation of the BRL.

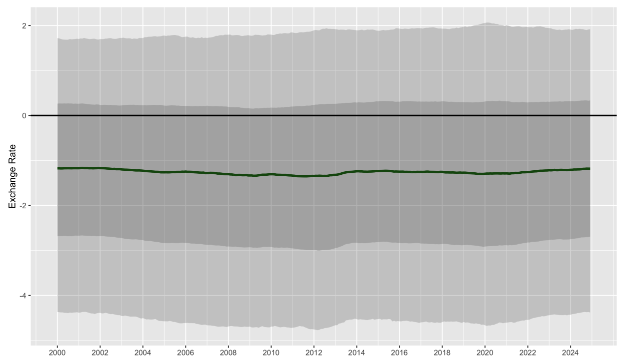
Thus, despite the opposite signs, the underlying currency movement remains aligned across models. Similarly, in the original model, a positive shock to the exchange rate variable (i.e., a depreciation of the BRL) led to a decline in the output gap and an increase in inflation. In the revised model, a positive shock to the effective exchange rate, interpreted as a BRL appreciation, has the opposite sign but mirrors the same economic relationship: it raises the output gap and reduces inflation.

Figure E.11: Impulse Responses for the Exchange Rate Channel in the Baseline Model

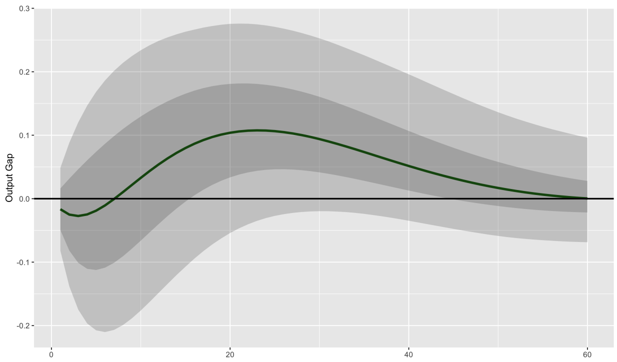
(a) Time-Invariant IRF: $\varepsilon_i \uparrow \rightarrow ex$



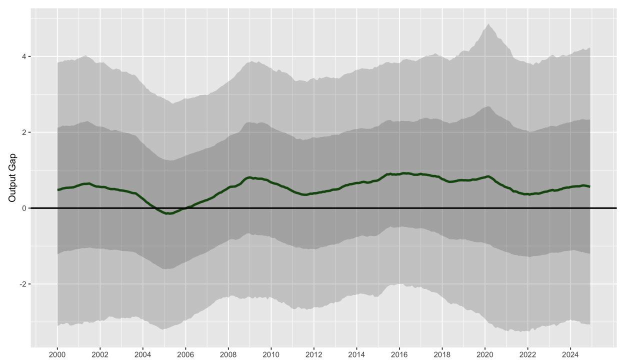
(b) Accumulated Time-Varying IRF: $\varepsilon_i \uparrow \rightarrow ex$



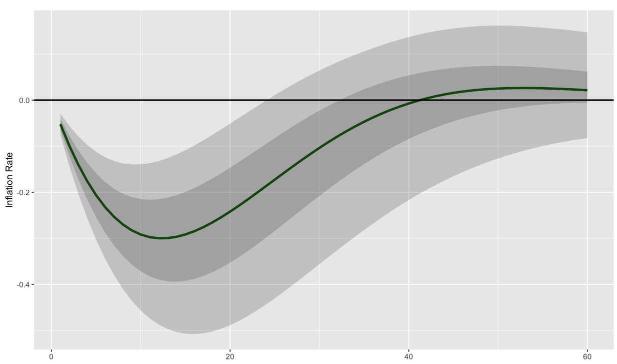
(c) Time-Invariant IRF: $\varepsilon_{ex} \uparrow \rightarrow \hat{y}$



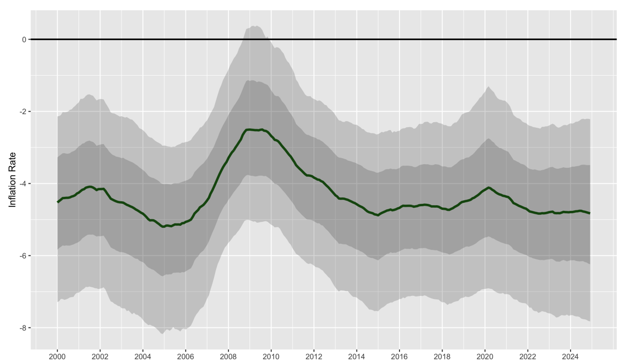
(d) Accumulated Time-Varying IRF: $\varepsilon_{ex} \uparrow \rightarrow \hat{y}$



(e) Time-Invariant IRF: $\varepsilon_{ex} \uparrow \rightarrow \pi$



(f) Accumulated Time-Varying IRF: $\varepsilon_{ex} \uparrow \rightarrow \pi$

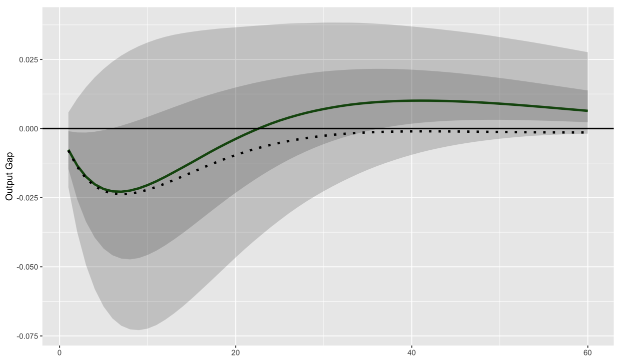


Note The figure presents the impulse response effects of a monetary policy rate shock (ε_i) on the exchange rate (ex) as well an exchange rate shock (ε_{ex}) on the output gap ($\hat{y}$) and inflation rate (π) response variables in the baseline model with effective exchange rate. For each variable, the left-hand panel displays the time-invariant average impulse response over a 60-month horizon, summarizing the IRF estimates across all time points. In contrast, the right-hand panel illustrates the accumulated 18-month impulse responses, highlighting the time-varying nature of the estimates. All panels include the 95% and 68% credible intervals.
Source: Own presentation of data collected from Banco Central do Brasil (2025a), Banco Central do Brasil (2025c), FRED (2025b), FRED (2025c), FRED (2025d), FRED (2025e), and World Bank Group (2025), compiled as indicated in Table 4.1 and processed in accordance with the methodology in Section 5.

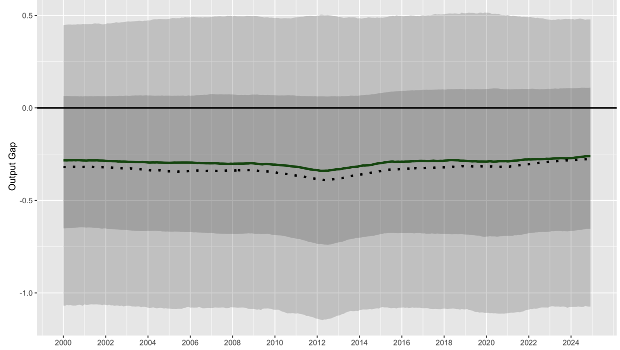
Although the sign of the exchange rate response differs due to the construction of the variable, the overall economic interpretation is preserved. This confirms that the exchange rate channel operates consistently across both specifications, further reinforcing the robustness of the model's transmission mechanisms.

Figure E.12: A Shock to the Monetary Policy Rate in the Model Excluding Exchange Rate

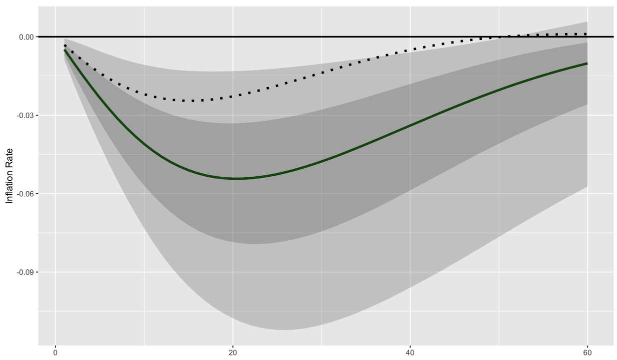
(a) Time-Invariant IRF: $\varepsilon_i \uparrow \rightarrow \hat{y}$



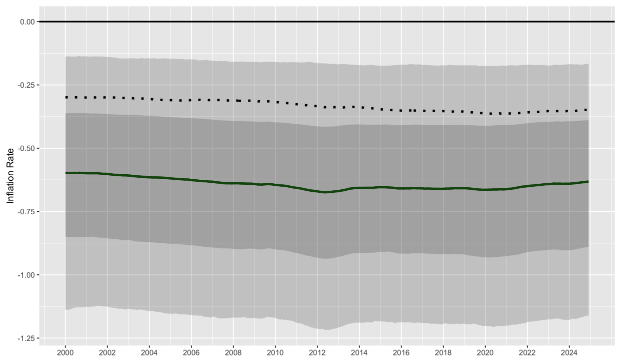
(b) Accumulated Time-Varying IRF: $\varepsilon_i \uparrow \rightarrow \hat{y}$



(c) Time-Invariant IRF: $\varepsilon_i \uparrow \rightarrow \pi$



(d) Accumulated Time-Varying IRF: $\varepsilon_i \uparrow \rightarrow \pi$

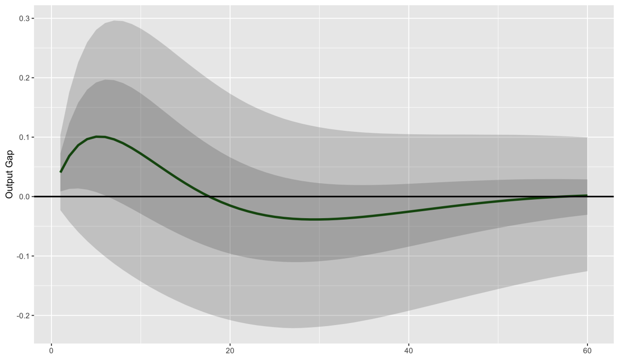


Note The figure presents the impulse response effects of a monetary policy rate shock (ε_i) on the output gap ($\hat{y}$) and inflation rate (π) response variables in the model with no exchange rate. For each variable, the left-hand panel displays the time-invariant average impulse response over a 60-month horizon, summarizing the IRF estimates across all time points. In contrast, the right-hand panel illustrates the accumulated 18-month impulse responses, highlighting the time-varying nature of the estimates. All panels include the 95% and 68% credible intervals as well as a dotted line for the corresponding impulse-response estimate in the baseline model.
Source: Own presentation of data collected from Banco Central do Brasil (2025a), Banco Central do Brasil (2025c), FRED (2025b), FRED (2025c), FRED (2025d), FRED (2025e), and World Bank Group (2025), compiled as indicated in Table 4.1 and processed in accordance with the methodology in Section 5.

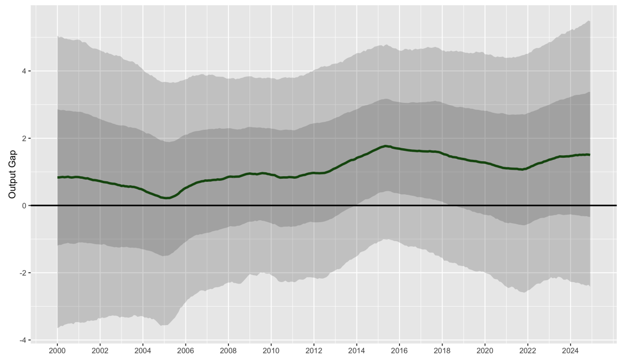
Additional support for the model's robustness comes from the versions excluding the exchange rate. As shown in Figure E.12 and Figure 6.4, the impulse responses of the output gap and inflation rate to a monetary policy shock remain virtually unchanged between the original and revised specifications. The responses are closely aligned in timing, suggesting that removing the exchange rate variable has no meaningful interaction with the change in measurement of the exchange rate. These consistent results indicate that the core transmission mechanisms linking monetary policy to inflation and output are structurally stable, even under different model assumptions.

Figure E.13: Impulse Responses for the Commodity Prices Channel in the Baseline Model

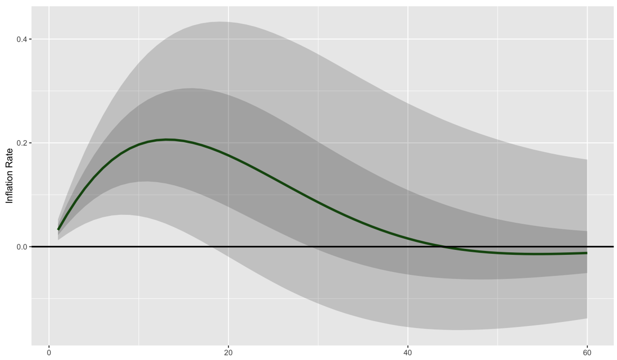
(a) Time-Invariant IRF: $\varepsilon_\psi \uparrow \rightarrow \hat{y}$



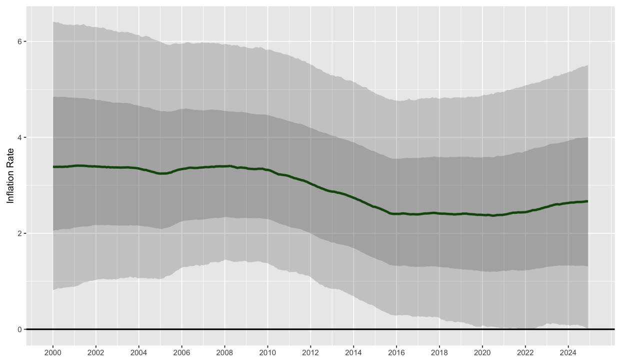
(b) Accumulated Time-Varying IRF: $\varepsilon_\psi \uparrow \rightarrow \hat{y}$



(c) Time-Invariant IRF: $\varepsilon_\psi \uparrow \rightarrow \pi$



(d) Accumulated Time-Varying IRF: $\varepsilon_\psi \uparrow \rightarrow \pi$



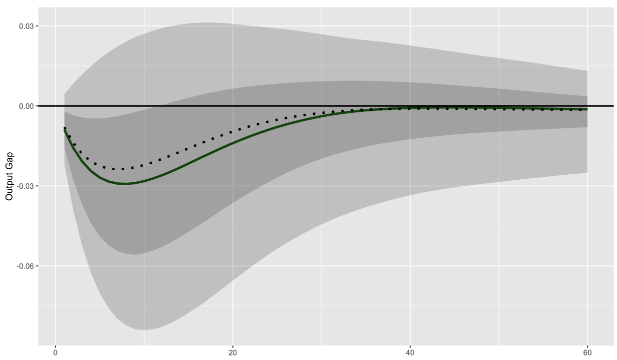
Note The figure presents the impulse response effects of a monetary policy rate shock (ε_i) on the commodity prices (ψ) as well a commodity price shock (ε_ψ) on the output gap ($\hat{y}$) and inflation rate (π) response variables in the baseline model with effective exchange rate. For each variable, the left-hand panel displays the time-invariant average impulse response over a 60-month horizon, summarizing the IRF estimates across all time points. In contrast, the right-hand panel illustrates the accumulated 18-month impulse responses, highlighting the time-varying nature of the estimates. All panels include the 95% and 68% credible intervals.

Source: Own presentation of data collected from Banco Central do Brasil (2025a), Banco Central do Brasil (2025c), FRED (2025b), FRED (2025c), FRED (2025d), FRED (2025e), and World Bank Group (2025), compiled as indicated in Table 4.1 and processed in accordance with the methodology in Section 5.

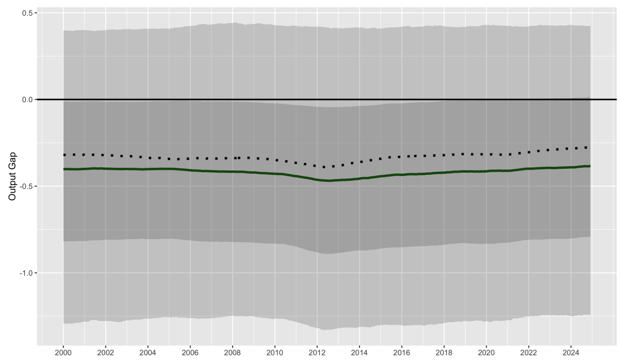
The baseline model's commodity price channel also appears unaffected by the change in the exchange rate measure. As illustrated in Figure E.13 and Figure 6.5, the influence on the output gap and inflation of commodity prices remains consistent across the two specifications. No significant differences are observed in either the direction or magnitude of the responses, indicating that the functioning of the commodity price channel is largely independent of how the exchange rate is defined. These results reinforce the robustness of the findings regarding the commodity price channel within the broader monetary transmission mechanism.

Figure E.14: A Shock to the Monetary Policy Rate in the Model Excluding Commodity Prices

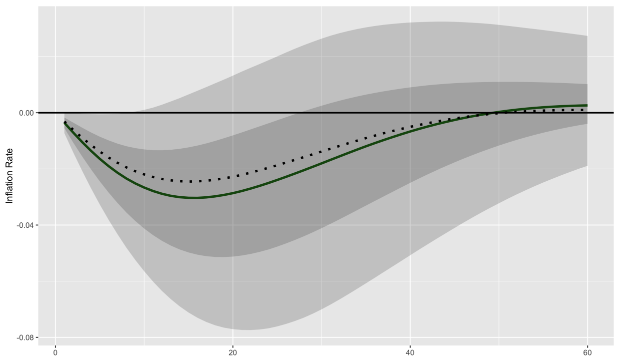
(a) Time-Invariant IRF: $\varepsilon_i \uparrow \rightarrow \hat{y}$



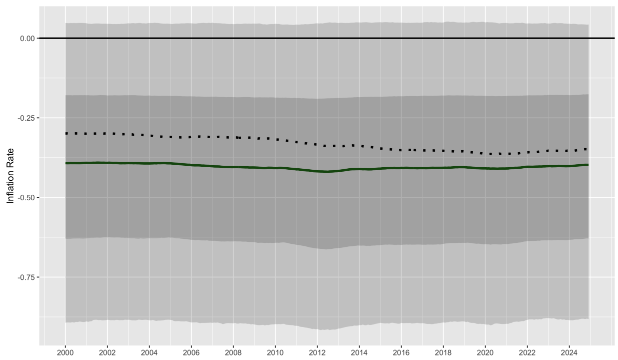
(b) Accumulated Time-Varying IRF: $\varepsilon_i \uparrow \rightarrow \hat{y}$



(c) Time-Invariant IRF: $\varepsilon_i \uparrow \rightarrow \pi$



(d) Accumulated Time-Varying IRF: $\varepsilon_i \uparrow \rightarrow \pi$



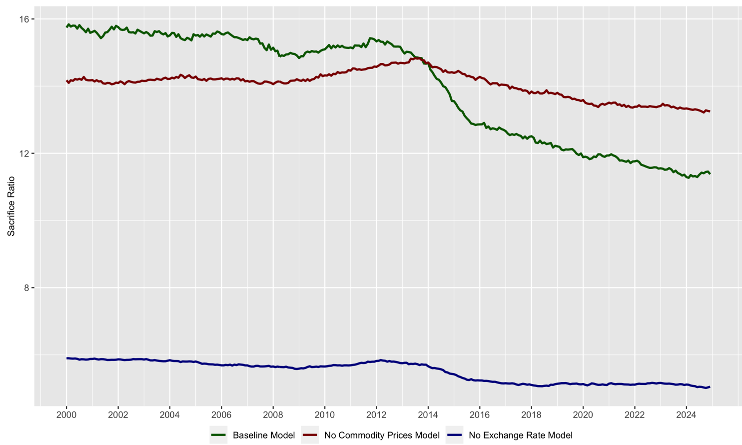
Note The figure presents the impulse response effects of a monetary policy rate shock (ε_i) on the output gap ($\hat{y}$) and inflation rate (π) response variables in the model with no commodity prices and effective exchange rate. For each variable, the left-hand panel displays the time-invariant average impulse response over a 60-month horizon, summarizing the IRF estimates across all time points. In contrast, the right-hand panel illustrates the accumulated 18-month impulse responses, highlighting the time-varying nature of the estimates. All panels include the 95% and 68% credible intervals as well as a dotted line for the corresponding impulse-response estimate in the baseline model.
Source: Own presentation of data collected from Banco Central do Brasil (2025a), Banco Central do Brasil (2025c), FRED (2025b), FRED (2025c), FRED (2025d), FRED (2025e), and World Bank Group (2025), compiled as indicated in Table 4.1 and processed in accordance with the methodology in Section 5.

The exclusion of the commodity price channel also has little impact on the transmission of monetary policy. As depicted in Figure E.14 and Figure 6.6, the responses of the output gap and inflation rate to a policy rate shock remain closely aligned across the two model specifications. The timing, direction, and magnitude of the effects are virtually unchanged, suggesting that the core mechanisms linking monetary policy to macroeconomic outcomes remain intact - even when commodity prices are omitted. This consistency further supports the robustness of the model's transmission framework.

E.2.3. Policy Trade-Off Analysis

To assess the robustness of the policy trade-off results, this section re-estimates the sacrifice ratio using the effective exchange rate in place of the BRL/USD rate and compares the findings to those from the original model specification. Across all models, the use of the effective exchange rate leads to a general increase in the level of the sacrifice ratio. Despite this shift, the dynamic patterns over time remain consistent with those observed in the original analysis. In both specifications, the baseline model begins in 2000 with the highest sacrifice ratio, but gradually becomes more efficient - outperforming the model excluding the commodity price channel in the later years of the sample.

Figure E.15: Sacrifice Ratio for All Model Specifications, 2000M1-2024M12



Note: The figure displays the monthly evolution of the sacrifice ratio from January 2000 to December 2024 across three TVP-SVAR-SV model specifications: the baseline model with effective exchange rate (green), the model excluding the exchange rate variable (blue), and the model excluding commodity prices but with effective exchange rate (red). In each case, the sacrifice ratio is computed as the cumulative response of the output gap relative to the level response of inflation 18 months after a monetary policy rate shock. Comparing the trajectories allows for an assessment of the exchange rate and commodity prices transmission channels alter the trade-off between disinflation and output loss.
Source: Own presentation of data collected from Banco Central do Brasil (2025a), Banco Central do Brasil (2025c), FRED (2025b), FRED (2025c), FRED (2025d), FRED (2025e), and World Bank Group (2025), compiled as indicated in Table 4.1 and processed in accordance with the methodology in Section 5.

As before, the model excluding the exchange rate consistently yields the lowest sacrifice ratio, indicating the most favourable inflation-output trade-off. While the switch in exchange rate measure introduces a level effect, it does not alter the relative behaviour or ranking of the models. Overall, these findings confirm that the conclusions drawn from the policy trade-off analysis are robust to the choice of exchange rate variable. The structural relationships and policy implications remain valid under this alternative specification.

E.3. Summary of Robustness Findings

The robustness analysis confirms the structural stability and reliability of the main empirical results. Both the alternative identification scheme and the use of an effective exchange rate measure yield impulse responses and policy trade-off dynamics that are consistent with those obtained from the original model specification. Minor quantitative variations were observed, particularly in level effects of the sacrifice ratio and convergence diagnostics, but these do not affect the qualitative conclusions. Across all checks, the transmission mechanisms from monetary policy to inflation and output remain intact. The behaviour of key channels proves stable across reasonable variations in identification strategy and variable operationalisations. Taken together, these findings support the conclusion that the baseline results are robust to alternative modelling assumptions and specification choices.