Can Fuel Policies Tame Exchange Rate Volatility? Fuel Policy Legacy in Brazil

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Abstract

We analyze volatility spillovers in fuel prices and the exchange rate in Brazil. Following Petrobras' adoption of import parity pricing (the state-owned oil company), we employ a partial connectedness measure (Chatziantoniou et al., 2023) and a structural vector autoregression (SVAR) to assess changes in transmission mechanisms of commodity shocks to the exchange rate and local fuel prices. We estimate the volatility using multivariate stochastic volatility (MSV). Understanding these effects is crucial for commodity-dependent economies to mitigate fuel price volatility and its inflationary pressures.

Keywords: fuel prices; volatility; spillover; commodity; country risk; exchange rate.

1 Introduction

The volatility of fuel prices is a phenomenon characterized by periodic occurrences. The response to these price movements varies across nations, with developing countries often resorting to the strategy of subsidizing retail prices (Kpodar and Imam, 2021). This approach, while providing a temporary buffer, has side effects. Clements et al. (2013) argued that subsidies

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can distort resource allocation by fostering energy consumption and diminishing incentives for renewable energy.

Brazil has experienced multiple instances of government interventions in the oil market as a subsidy strategy to alleviate international fuel price pressures. The government indirectly controls prices through the state-owned oil producer—Petrobras—given its status as the primary shareholder (Hallack et al., 2020) and the dominant fuel supplier in Brazil, commanding over 80% of the market share (Nascimento Filho et al., 2021). As illustrated by Khanna et al. (2016), the establishment of a reference price serves as a *de facto* cap on the domestic wholesale oil price. In 2013, for instance, the national wholesale price was approximately 30% below the import parity reference price in the Gulf of Mexico. In 2016, following the impeachment of the Brazilian president, the new government liberalized the oil pricing policy, with the Petrobras CEO declaring that prices would be set according to international oil price fluctuations through the import parity price (IPP) of oil.

While a notable body of literature has examined the relationship and pass-through effects between international oil and domestic fuel prices (i.e., gasoline and ethanol) during the IPP period (Palazzi et al., 2022; Hallack et al., 2020), the policy's implication on the exchange rate remains unexplored. This gap motivates our study, the first to analyze not only how international oil price shocks influence domestic fuel prices but also how the implementation and subsequent dismantling of IPP reshaped the nexus between oil prices and the foreign exchange market. We identify a primary channel through which oil price shocks may impact the exchange rate: the country risk premium. Our comprehensive dataset spans the key periods concerning the fuel price policy, encompassing both the post-monopoly era (2004-2016) and the IPP period until its official discontinuation in 2023.

Our research approach builds upon the established commodity currency literature (Chen and Rogoff, 2003) to understand the interplay between commodity prices and exchange rates. We then develop a theoretical foundation based on the uncovered interest rate parity (UIP) approach proposed by Galí (2020) and extend this model to account for the country risk premium. We posit that the country risk premium can have an anticipated effect on the exchange rate mediating the effect of the fuel shocks.

To empirically investigate the spillover effects of the fuel price volatility on the exchange rate volatility before and after the IPP implementation, we employ two distinct methodologies. First, we employ the partial connectedness measure proposed by Chatziantoniou et al. (2023). This model is an advancement of decomposed connectedness measures, allowing for the analysis of spillovers in internal and external groups (Gabauer and Gupta, 2018). The key advantage of partial connectedness lies in its ability to isolate the net effect of fuel price shocks on exchange rates, excluding the influence of risk factors (GSCI and CDS). This is achieved by separating the connectedness table into two parts: inclusive and exclusive connectedness measures. To do so, we collect the following prices: (i) the domestic retail prices of diesel, gasohol (gasoline mixed with ethanol anhydrous), and hydrous ethanol; (ii) the real effective exchange rate (REER); and (iii) the country risk premium using the Brazilian CDS as a proxy. To estimate the volatility, we employ the multivariate stochastic volatility (MSV) proposed by Kastner et al. (2017). Second, we conduct a Structural Vector Autoregression (VAR) analysis to examine the impact of the country risk premium on the exchange rate before and after the implementation of the IPP, as well as the effects of the S&P Goldman Sachs Commodity Index (GSCI).

Our analysis indicates a significant decrease in ethanol volatility following the implementation of the IPP. Conversely, diesel volatility exhibited sporadic spikes in 2018 and 2023. Regarding the connectedness measures, our preliminary findings highlight a distinct shift in spillover effects before and after the IPP. Prior to the policy's implementation, CDS, gasoline, and diesel prices were the primary drivers of REER volatility. However, post-IPP, the CDS emerged as an additional significant contributor, accompanied by a decrease in diesel's contribution and a slight increase in ethanol spillover. Remarkably, the REER's sensitivity to various factors intensified under the IPP. Interestingly, when isolating the dynamics of risk factors (CDS and GSCI), we observed a reduced contribution of domestic fuel prices to the overall system post-IPP, with the exception of ethanol. This observation aligns with the anticipated impact of the IPP, which emphasizes the influence of international price signals in domestic fuel price determination. On top of that, we observed a more pronounced effect of the GSCI on the REER.

The results from the SVAR indicate an increasing sensitivity of the REER to shocks originating from the CDS and GSCI. Additionally, we observed a lasting effect of the GSCI on the interest rate differentials, more than doubling post-IPP. These SVAR findings are consistent with the results obtained using the partial connectedness approach, suggesting that the risk factors associated with fuel prices and the REER became more interconnected after the IPP implementation. However, it's worth noting that despite the IPP, we still observed some government interventions that may have attenuated certain effects, such as Central bank intervention in the foreign exchange (FX) market and diesel price controls in late 2018

Our contribution to the literature is distinctive in unraveling the volatility dynamics under two distinct fuel price policies in Brazil, a country that is not only a major petroleum producer but also the second-largest ethanol producer globally. Notably, Brazil is one of the largest consumers of ethanol for cars, with more than 80% of its vehicle fleet being fuel-flexible, meaning that consumers can choose either gasoline or ethanol in any proportion (Palazzi et al., 2022). Therefore, our study serves as a roadmap for policymakers to understand the intricate transmission of fuel volatility not only into domestic prices but also into exchange rate fluctuations. Commodity countries with significant oil dependence can benefit from our findings, particularly regarding potential policy choices and their impact on volatility under different fuel price regimes. At the firm level, traders and risk managers can leverage our analysis to inform their positioning and risk management strategies in light of fluctuating fuel prices and potential policy shifts.

2 Background

2.1 Brazil fuel price policy context

Brazil is recognized as an important agricultural commodity producer. However, in recent years, the country's significance as an oil producer has also grown, fueled by the discovery and extraction of oil reserves.[1] The country achieved self-sufficiency after 2007 with a ma-

[1] Brazil received an invitation to join OPEC+ in 2023, a group formed by 23 countries that collectively produce approximately 40% of global oil production. See: `https://agenciabrasil.ebc.com.br/en/economia/noticia/2023-12/brazil-could-join-group-oil-producers-exporters`

jor oil reserve discovery known as the "Pre-Salt layer" (Magalhães and Domingues, 2014). Nevertheless, in 2023, its production experienced the highest increase to date, with a 13% increment from 2022 to 2023, nearly doubling its production since the discovery of the Pre-Salt oil reserves (ANP, 2023). Despite its prominent position as a leading global oil producer, understanding the pricing policy and risk management remains a complex and critical challenge.

To grasp Brazil's intricate price policy, it is essential to trace the trajectory of the state-owned company since its establishment in 1954. Petrobras holds a dominant position in Brazil's oil industry, engaging in the exploration, production, refining, and distribution of oil products. Initially, the company operated as a monopoly, controlling exploration, extraction, and refining to reduce oil imports and bolster the industrial sector. During this period, government oversight of oil products was direct. However, a significant shift occurred in 1997 with the approval of the Petroleum Law (9.478) by Congress, which aimed to liberalize the sector pertaining to oil product production (Bridgman et al., 2011). According to Almeida et al. (2015), this legislation ushered in a gradual process of price liberalization, marked by the phasing out of subsidies to align domestic prices with international ones, culminating in full price liberalization by 2002.

While Petrobras does not directly control gasoline prices, notable policy interventions occurred, particularly during 2013-2014. The company's ability to set a cap on gasoline prices stems from two key factors: First, Petrobras commands over 80% of the market share for Gasoline A and supplies the distribution chain, and second, the federal government holds the majority of its shares (Nascimento Filho et al., 2021). According to Hallack (2020), the government's majority ownership of Petrobras shares enables indirect control over gasoline prices. Consequently, the company leverages this position to mitigate energy price volatility and curb inflation. Furthermore, a persistent deficit existed between the import parity price (the cost of importing gasoline) and the local reference price, accumulating in an "oil account" since the 1980s, reaching 30% in 2013 (Khanna et al., 2016). Costa and Burnquist (2016), in turn, demonstrate that the price cap was only evident after 2011. Thus, between 2008 and 2010, import parity prices were lower than domestic prices, possibly incentivizing ethanol production. However, a policy shift occurred between 2011 and 2014, with the government heavily influencing prices by setting them below international references and even reducing fuel taxes to zero in 2013-2014. Fig.1 illustrates Brazilian fuel subsidy spending from 2010 to 2022. Petroleum subsidies peaked in 2011 but fell significantly in 2015 (-45%), coinciding with the beginning of the implementation of the IPP policy in 2016.

Following a net loss of BRL 35 billion in 2015 as a consequence of the price control (Almeida et al., 2015), Petrobras began to adjust its gasoline prices in line with international prices. This adjustment took place amidst high inflation, compelling the government to reconsider its pricing strategy. In 2016, Petrobras's newly appointed CEO announced a departure from government interference, signaling a commitment to setting gasoline prices in accordance with international references, incorporating the import parity price (IPP) and a risk-adjusted spread (Nascimento Filho et al., 2021). It is worth mentioning that, this mechanism of price adjustment, which had no defined periodicity, included not only oil fluctuations on the international market but also exchange rate variations. [2] However, the IPP policy suffered its first setback in 2018. The significant increase in the price of oil on the international market forced Petrobras to make multiple adjustments in a short period of time. This series of adjustments precipitated

[2] The methodology was not disclosed by the company. See: https://noticias.uol.com.br/comprova/ultimas-noticias/2023/05/24/entenda-as-politicas-de-precos-da-petrobras.htm

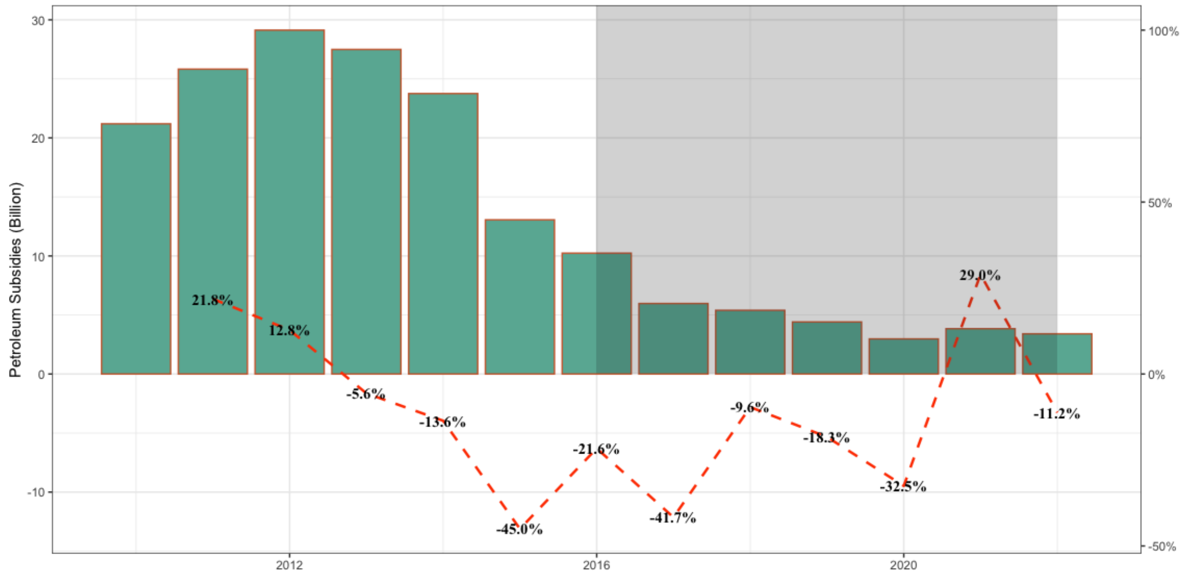


Figure 1: Estimates of subsidies to petroleum in Brazil. The shaded region in gray depicts the IPP policy period. Source: OECD, IEA, IMF, UN, World Bank

a nationwide truckers' strike, prompting government intervention to cap diesel price hikes and reduce the frequency of price adjustments (Palazzi et al., 2022). Another significant event occurred in 2022 when escalating tensions between Russia and Ukraine led to a surge in oil prices, prompting Petrobras to once again review its pricing policy. Soon after, in May 2023, Petrobras announced the ending of the IPP policy.

2.2 Commodities currency context

To understand the interplay between fuel price volatility, the REER, the CDS, and the GSCI, particularly in the context of pre- and post-IPP policy periods, we examine the literature on commodity currencies, focusing on how risk factors (GSCI and CDS) affect the REER and fuel prices through spillover effects. Our key research question is to identify the main channels through which commodity price uncertainty can impact local fuel prices and the real exchange rate in these two periods.

We start by discussing the effects of what are called commodity currencies, where fluctuations in real commodity prices can explain changes in the real exchange rates in nations with substantial commodity export shares. For instance, Chen and Rogoff (2003) uncover evidence suggesting that commodity prices, denominated in US dollars, exert influence on the real exchange rates. While their study focused solely on Australia, Canada, and New Zealand, Cashin et al. (2004) expanded the scope by exploring the long-term relationship between the real exchange rate and real commodity prices across 58 countries. Among these, 19 countries exhibited a robust relationship, with over 85% of their real exchange rate fluctuations attributed to movements in real commodity prices. Bodart et al. (2012) argues that the greater a country's export share of commodities, the more pronounced the impact on its real exchange rate, suggesting the presence of Dutch Disease effects in these nations. For Brazil specifically, Kohlscheen (2014) illustrates a long-term relationship between the Brazilian REER and the price variation of a basket composed of five commodities representing over 50% of Brazilian export revenues. The author attributes the discovery of Pre-Salt oil reserves and the increasing exports of fuel and iron ores as potential drivers of the Brazilian exchange rate variation.

Other studies highlight the predictive power of oil prices in forecasting exchange rate movements. For example, Chen and Chen (2007) document real oil prices as the primary driver of real exchange rate fluctuations, as well as their ability to predict future exchange rate returns. In the same vein, Salisu et al. (2021) apply symmetric and asymmetric prediction models to forecast exchange rates based on oil prices. Their findings indicate that the symmetric model successfully predicts Brazil's exchange rate return, while the asymmetric model suggests that the exchange rate tends to appreciate in response to positive oil price fluctuations. However, for negative oil prices, the effect is similar, though the authors argue that this behavior is expected since Brazil tends to stabilize its exchange rate through market interventions. These effects may be related to the monetary policy in countries that have adopted inflation targeting (IT). Frankel (2010) highlights that Latin American countries, particularly Brazil, Chile, and Peru, which have adopted IT, tend to respond to oil shocks by tightening monetary policy, leading to the appreciation of their currencies. Bodart et al. (2012) suggests a contrasting approach, arguing that countries susceptible to Dutch Disease effects should actually ease monetary policy during surges in commodity prices. Notably, in the 1990s, many countries, particularly emerging economies, adopted IT as a monetary policy strategy to reduce and stabilize inflation. Following its success in New Zealand, several emerging economies implemented IT, including Brazil in 1999. This positive outcome is emphasized by Coulibaly and Kempf (2019), showing evidence that the emerging economies that implemented IT lowered their level and volatility of inflation. However, Aizenman et al. (2011) argue that emerging market central banks may not follow a "pure" IT strategy. They point out that these central banks tend to react by determining interest rates not only for inflation but also for the real exchange rate. This is because countries heavily reliant on commodity exports are more vulnerable to fluctuations in terms of trade, making the real exchange rate a significant concern for their monetary policy.

Notwithstanding, the effectiveness of IT as a tool for curbing inflation in emerging markets was challenged in the wake of the sub-prime crisis and heightened volatility in financial markets. The increased correlation between markets led to significant spillover effects from oil shocks, impacting not only commodity-dependent nations but also economies globally.[3] Financialization, the increasing involvement of financial institutions in commodity markets, has played a role in this. Tang and Xiong (2012) underscore the impact of financialization since the early 2000s, noting how the influx of index investment into the commodity markets has led to a growing co-movement between oil prices and non-energy commodity futures prices in the United States. Furthermore, Peersman et al. (2021) explain how informational frictions worldwide contribute to the impact of oil shocks on inflation. While the financialization of the commodity in the 2000s improved information discovery, it also facilitated spillover effects between markets. For instance, the authors observed that oil shocks were more pronounced during periods characterized by stronger pass-through effects to other commodity prices, Ding et al. (2023) emphasize this argument by showing the pass-through effect of high oil prices on China's exchange rate as the main driver of domestic inflation. The authors advise the use of foreign exchange reserves to stabilize inflation and reduce the covariance between oil prices

[3] A debate exists on the impact of speculation on commodity price volatility, as explored by Irwin and Sanders (2012, 2011)

and exchange rates for countries with IT.

The CDS serves as another critical risk factor in comprehending exchange rate dynamics. Existing literature sheds light on the relationship between CDS and exchange rates. For instance, Calice and Zeng (2021) demonstrate that the sovereign CDS term premium serves as a reliable predictor of exchange rates. Similarly, Feng et al. (2021) uncover a close relationship between CDS and exchange rates, with the latter indicating a higher spillover effect on the former. Hence, our objective is to investigate whether these relationships hold true within the Brazilian context across two distinct periods: one characterized by government interventions in fuel prices, and another marked by reduced government interference, or at least, a decrease in its level of intervention.

3 Theoretical framework

To investigate the risk factors on the exchange rate and the fuel prices in Brazil, we built our framework based on the components of currency risk. To derive the country risk premium, we rely on the work proposed by Garcia and Olivares (2001) and Garcia and Brandao (2001). Following the covered interest rate parity (CIP), the domestic interest rate i is expressed as:

$$i = i^* + (f - s) + cr \tag{1}$$

where i denotes the domestic interest rate, i^* denotes the foreign interest rate, f represents the first future contract of the exchange rate, and cr accounts for the country risk. We can write the forward premium (the expected depreciation at time t) and currency risk as:

$$(f - s) = \mathbb{E}(s_T - s_t) + cp \tag{2}$$

Consequently, the country's risk can be reconfigured as:

$$i = i^* + \mathbb{E}(s_T - s_t) + cp + cr \tag{3}$$

Rearranging, we obtain an expression for the country risk premium cr:

$$cr = i - i^* - (f - s) \tag{4}$$

This separates the country risk into the interest rate differential component and the forward premium component.[4] Garcia and Olivares (2001)define the country risk as a convenience yield rate (y), representing the covered interest rate parity differential, such that:

$$F = S e^{(r - r^* - y)(T - t)}$$

[4] The country risk premium cr can be also gauged by examining the yields on dollar-indexed local bonds ("cupom cambial"). This yield can be dissected into: $cc = i^* + cr$. Where, cc represents the cupom cambial. One can distinguish the country's risk premium component by comparing yields from equivalent foreign bonds with those of dollar-indexed domestic bonds. The cc is a future contract characterized by its high liquidity, with daily trading volume hovering at around \$7 million on the Brazilian Exchange (B3).

rearranging the terms (Coelho dos Santos et al., 2016),

$$s_t + (r_t - r_t^* - y_t)(T - t) = E_t(s_{t+1}) + \mathrm{cr}_t$$

Our next goal is to write the interest rate differential in real terms. To do so, we take into account the Galí (2020) work and extend to include the country risk. The author considers the price index (P_t) for consumption goods and the nominal exchange rate as ε_t.

$$\mathbb{E}_t\left\{\Lambda_{t,t+1}\frac{P_t}{P_{t+1}}[(1+i_t) - (1+i_t^*)\frac{\varepsilon_{t+1}}{\varepsilon_t}]\right\} = 0 \tag{5}$$

where $\Lambda_{t,t+1}$ is the real stochastic discount factor for a domestic investor with restricted access to the two bonds in t time. Then, the author applies a first-order condition in the previous Equation, such that $i = i^* + \mathbb{E}(\Delta e_{t+1})\forall t$, resembling the UIP condition. Thus, the equation in real terms, considering $q_t \equiv p_t^* + e_t - p_t$ as the real exchange rate, can be described as follows:

$$q_t = r_t^* - r_t + \mathbb{E}_t\{q_{t+1}\} \tag{6}$$

Equation 6 is denoted by the real interest rate $r_t \equiv i_t - \mathbb{E}\{\pi_{t+1}\}$ and the inflation (CPI) as $\pi_t \equiv p_t - p_{t-1}$, where r^* and π_t^* represent the foreign economy indices. We can now replace the UIP condition in the model with this new relationship that incorporates the country risk components explicitly:

$$q_t = r_t^* - r_t + \mathbb{E}_t[q_{t+1}] - cr_t \tag{7}$$

This modification introduces a time-varying country risk premium, influenced by interest rate differentials and forward premia. We define the real exchange rate as a function of current and expected real interest rate differentials, as well as the long-run expectation of the real exchange rate. To achieve this, we derive equations analogous to those presented in Galí (2020), explicitly incorporating the country risk premium cr_t. Therefore, assuming that the $\lim_{T\to+\infty}\mathbb{E}_t\{q_T\}$ is well-defined and bounded, Equation 7 can be solved recursively, yielding:

$$q_t = \lim_{T\to\infty}\mathbb{E}_t\{q_T\} + \sum_{k=0}^{\infty}\mathbb{E}_t[r_{t+k}^* - r_{t+k} - cr_{t+k}] \tag{8}$$

A caveat of the model is that it relies on the subjective expectation $\tilde{\mathbb{E}}_t\{\cdot\}$, which must adhere to the law of iterated expectation and the transversality condition concerning the real exchange rate.

$$q_t = \bar{\mathbb{E}}_t\{q_T\} + \sum_{k=0}^{\infty}\mathbb{E}_t[r_{t+k}^* - r_{t+k} - cr_{t+k}] \tag{9}$$

$$q_t = \lim_{T\to\infty} \mathbb{E}_t\{q_T\} + \sum_{k=0}^{\infty} \mathbb{E}_t[r^*_{t+k} - r_{t+k} - cr_{t+k}]$$

Specifically, we can assume that the real interest rate differential ($r^*_{t+k} - r_{t+k}$) and the country risk premium (cr_{t+k}) follow stationary AR(1) processes:

$$r^*_{t+k} - r_{t+k} = \rho(r^*_{t+k-1} - r_{t+k-1}) + \varepsilon^r_{t+k} cr_{t+k} = \varphi cr_{t+k-1} + \eta_{t+k}$$

where ρ and φ are the AR(1) coefficients, and ε^r_{t+k} and η_{t+k} are the white noise shock processes for the real interest rate differential and the country risk premium, respectively.

Under these assumptions, we can express the infinite sum as:

$$\sum_{k=0}^{\infty} \mathbb{E}_t[r^*_{t+k} - r_{t+k} - cr_{t+k}] = \mathbb{E}_t[\varepsilon^r_t] + \sum_{k=1}^{\infty} \rho^k \mathbb{E}_t[\varepsilon^r_{t+k}] - \mathbb{E}_t[\eta_t] - \sum_{k=1}^{\infty} \varphi^k \mathbb{E}_t[\eta_{t+k}]$$

Since ε^r_{t+k} and η_{t+k} are white noise processes, their expected values are zero for $k > 0$. Therefore, the infinite sum simplifies to:

$$\sum_{k=0}^{\infty} \mathbb{E}_t[r^*_{t+k} - r_{t+k} - cr_{t+k}] = \varepsilon^r_t - \eta_t$$

Substituting this back into the original equation, we get:

$$q_t = \lim_{T\to\infty} \mathbb{E}_t\{q_T\} + \varepsilon^r_t - \eta_t \tag{10}$$

This equation expresses the current value of q_t in terms of the expected future value of q_T (as T goes to infinity), and the current shocks to the real interest rate differential and the country risk premium. This formulation simplifies the analysis of exogenous shocks to the country risk premium (denoted by $\Delta\eta_t$). In essence, a change in the country risk premium ($\Delta\eta_t$) will affect the current value of the country risk premium (cr_t), which in turn influences the current value of q_t.

Suppose an AR(1) process for the country risk:

$$cr_{t+k} = \varphi cr_{t+k-1} + \eta_{t+k} \tag{11}$$

A shock to η_t will affect cr_t as follows:

$$cr_t = \varphi cr_{t-1} + \eta_t + \Delta\eta_t$$

Thus, this shock will also affect the infinite sum in the equation for q_t:

$$\sum_{k=0}^{\infty} E_t[r^*_{t+k} - r_{t+k} - cr_{t+k}] = \varepsilon^r_t - \eta_t - \Delta\eta_t$$

Substituting this back into the equation for q_t, we get:

$$q_t = \lim_{T\to\infty} E_t\{q_T\} + \varepsilon^r_t - \eta_t - \Delta\eta_t \tag{12}$$

Equation (12) depicts the impact of a shock to the country risk premium (cr) on the current value of q_t. This equation suggests that an increase in cr (positive shock) leads to a decrease in the current value of q_t ($\frac{\partial\Delta\eta_t}{\partial q_t} = -1$), all else being equal.

4 Methodology

4.1 Multivariate factor stochastic volatility (MSV) model

The SV is modeled as an unobserved latent variable. SV overcomes the GARCH model by better capturing the properties of financial time series (Broto and Ruiz, 2004). While GARCH models capture the changes in volatility over time by letting the conditional variance be a function of the squares of previous observations and past variances, SV is modeled as a linear stochastic process that contains an unobserved variance component. One of its main disadvantages is the difficulty of estimating the maximum likelihood (Harvey et al., 1994). Alizadeh et al. (2002) demonstrate that despite the use of the Gaussian quasi-maximum likelihood estimation (QMLE) to model SV, the log absolute or squared returns are affected by non-Gaussian measurement errors that not only produce highly inefficient estimators from the QMLE but also lead to inefficient inferences about latent volatility. Nonetheless, Broto and Ruiz (2004) point out the advancement of numerical methods based on the MCMC process that can solve a high dimensional integral, and its inference is based on finite sample distributions. This allows for more accurate inference about model parameters and helps to smooth out the parameter estimates.

The main characteristic of the SV model is that volatility is driven by its own stochastic process. Following Hosszejni and Kastner (2021), given a vector of observations $\mathbf{y} = (y_1, \ldots, y_n)^\top$, in which $\mathbf{y}$ takes the structured form as follows:

$$y_t = \mathbf{x}_t^\top \boldsymbol{\beta} + \exp\left(\frac{h_t}{2}\right)\varepsilon_t, \tag{13}$$

$$h_{t+1} = \mu + \varphi(h_t - \mu) + \eta_t, \tag{14}$$

where:

i $\varepsilon_t \sim \mathcal{N}(0, 1)$ and $\eta_t \sim \mathcal{N}(0, 1)$ are independent and identically distributed (i.i.d.) standard normal random variables.

ii $\mathcal{N}(b, B)$ denotes the normal distribution with mean $b \in \mathbb{R}$ and variance $B \in \mathbb{R}^+$.

iii $h = (h_1, \ldots, h_n)^\top$ is the log-variance process, initialized by $h_0 \sim \mathcal{N}\left(\mu, \frac{\sigma^2}{1-\phi^2}\right)$.

iv $\mathbf{X} = (\mathbf{x}_1^\top, \ldots, \mathbf{x}_n^\top)^\top$ is an $n \times K$ matrix, where the t-th row $\mathbf{x}_t^\top$ contains the K regressors at time t.

v $\boldsymbol{\beta} = (\beta_1, \ldots, \beta_K)^\top$ is the K-dimensional vector of regression coefficients.

vi $\boldsymbol{\vartheta} = (\mu, \varphi, \boldsymbol{\theta})$ is the collection of SV parameters, where μ is the level, φ is the persistence, and $\boldsymbol{\theta}$ (also called volvol) is the vector of standard deviations of the log-variance process.

In this simple form, the observations y_t are conditionally heteroscedastic, with time-varying volatility governed by the log-variance process h_t. The log-variance process is a first-order autoregressive process with Gaussian innovations, where μ represents the long-run mean, and φ controls the persistence of deviations from the long-run mean.

To analyze the volatility of the variables, we employ the multivariate stochastic volatility (MSV) model following the implementation of Hosszejni and Kastner (2021). The implementation of the MSV factor provided by Hosszejni and Kastner (2021) is an advancement of the Kastner (2016) model that incorporates leverage effect as well as multivariate generalization. The MSV model proves efficient in understanding how the entire system, composed of different assets, can share similar components of each other's volatility defined by the latent factor. Each asset's volatility can be decomposed into common and idiosyncratic factors, where the latter captures its own process without being influenced by other assets. The MSV model captures not only how both factors can affect individual volatility but also how changes in market conditions affect the volatility of the assets (Ghaemi Asl et al., 2023). Harvey et al. (1994) argue that the MSV has the advantage of capturing co-movements in volatility, allowing variances and covariances to evolve dynamically over time.

The "curse of dimensionality" is one of the problems dealing with a high number of unknown observations over the total number of observations in the multivariate case. Kastner (2019) suggest using the factor SV models to decomponse the $m \times m$ covariance matrix Σ_t with $m(m+1)/2$ elements into a factor loadings matrix Λ of size $m \times r$, an r-dimensional diagonal matrix V_t and an m-dimensional diagonal matrix U_t, such that $\Sigma_t = \Lambda V_t \Lambda^\top + U_t$, reducing the number of free elements to $mr + m + r$. Hosszejni and Kastner (2021) demonstrate that some identification problems may appear, such as the unidentified scale of the factors, which is solved by fixing the level of their log-variance to zero. The next step is specifying the priors for the mean, the latent log-variance process, and the factor loading matrix $\mathbf{\Lambda}$ by selecting the $\beta_j \sim \mathcal{N}(b_\beta, B_\beta)$ independently for $j = 1, \ldots, m$. Finally, the package **factorstochvol** executes the Bayesian estimation of the SV factor. This execution is based on the Kastner et al. (2017) study that propose an efficient Bayesian MCMC algorithm that enhances the mixing of draws obtained from the posterior distribution for the factor loading matrix. In the next section, we develop the empirical framework, using the involved variables.

4.2 Connectedness measure

To capture the spillover effects and the interconnectedness between the involved variables before and after the IPP policy, we rely on the Chatziantoniou et al. (2023) partial connectedness approach. This method improves on the Diebold and Yilmaz (2012); Diebold and Yılmaz (2014) work by accounting for time variation on the VAR coefficients. Moreover, this approach minimizes the loss of observations during the fitting process. Another advantage is no need to set arbitrarily the rolling windows' size. The TVP-VAR selection process is based on the Bayesian information criteria (BIC) with the following form (Antonakakis et al., 2020):

$$Y_t = \beta_t Y_{t-1} + \varepsilon_t \varepsilon_t \sim N(0, S_t) \tag{15}$$

$$\beta_t = \beta_{t-1} + v_t v_t \sim N(0, R_t) \tag{16}$$

$$Y_t = A_t \varepsilon_{t-1} + \varepsilon_t \tag{17}$$

Where Y_t, ε_t, β_t, and v_t are vectors, and A_t, S_t, and R_t are matrices. Eq. (5) denotes the Wold system (Antonakakis et al., 2018).

The model is drawn upon the generalized impulse response function (GIRF) and the generalized forecast error variance decomposition (GFEVD) (Pesaran and Shin, 1998; Koop et al., 1996), where the time-varying coefficients of the vector moving average (VMA) needs to be transformed into TVP-VMA. GFEVD is applied to explain the variance share variable i on variable j— the one step ahead (h) of variable i related to the shock on variable j— which can be described as follows:

$$\tilde{\psi}^g_{ij,t}(H) = \frac{\psi^g_{ij,t}(H)}{\sum_{k=1}^{j} \phi^g_{ij,t}(H)} \tag{18}$$

where, $\psi^g_{ij,t}(H)$ being the effect of j on i related to its forecast error variance share and each row equals to 1, with $\sum_{j=1}^{k} \tilde{\psi}^g_{ij,t}(H) = 1$, $\sum_{i,j=1}^{k} \tilde{\psi}^g_{ij,t}(H) = k$. The forecast horizon is denoted by H.

We compute the directions of the spillover. First, the effect of a shock in series i on the rest of the series j, called total directional connectedness **to** others:

$$TO_{it}(H) = \sum_{j=1, i\neq j}^{k} \tilde{\psi}^g_{ji,t}(H) \tag{19}$$

Second, the impact of the overall series j on i— the total directional connectedness **from** others:

$$FROM_{it}(H) = \sum_{j=1, i\neq j}^{k} \tilde{\psi}^g_{ij,t}(H) \tag{20}$$

The difference between $TO_{it}(H)$ and $FROM_{it}(H)$ is the net effect of i on the specific network (**net** total directional connectedness), described as follows:

$$NET_{it}(H) = TO_{it}(H) - FROM_{it}(H) \tag{21}$$

This measure will indicate whether the time series acts as a transmitter or receiver of shocks, as well as the magnitude of the shock transmission.

Next, following Gabauer (2021), we compute the total connectedness index (TCI) to describe the degree of market risk. The author demonstrates that interpreting the TCI within the range $[0, \frac{m-1}{m}]$ based on Monte Carlo simulation is somewhat difficult. Thus, the TCI can be decomposed into pairwise connectedness (PCI) between series i and j.

Our study aims to assess shock transmission within both internal and external groups. We adopt the decomposed approach outlined by Gabauer and Gupta (2018), which breaks down the connectedness measures presented in Table $\Phi(H)$ into K groups of risk factors (CDS and GSCI), along with the REER and fuel prices. The authors organized this decomposition in a matrix described as follows:

$$\Phi_t(H) = \begin{bmatrix} C^{\alpha}_{11t}(H) & C^{\alpha}_{12t}(H) & \dots & C^{\alpha}_{1Kt}(H) \\ C^{\alpha}_{21t}(H) & C^{\alpha}_{22t}(H) & \dots & C^{\alpha}_{2Kt}(H) \\ \vdots & \vdots & \ddots & \vdots \\ C^{\alpha}_{K1t}(H) & C^{\alpha}_{K2}(H) & \dots & C^{\alpha}_{KKt}(H) \end{bmatrix} \tag{22}$$

where $C^{\alpha}_{II}(H)$ includes the internal spillovers of group I and $C^{\alpha}_{IJ}(H)$, $I \neq J$, denotes the external spillovers of group J to group I. Thus, $TCI^{int}II, t(H)$ indicates the internal spillovers of group I at time t, and the group-external total connectedness index, denoted as $TCI^{ext}t(H)$. We can get the original $TCI_t(H)$ by computing the weighted sum of the $TCI^{int}II, t(H)$, such that $TCI^{int,agg}t = \sum_{I=1}^{K} \frac{l_I}{k} \cdot TCI^{int}_{II,t}(H)$. Hence,

$$TCI_t(H) = TCI^{ext}_t(H) + TCI^{int,agg}_t$$

The Chatziantoniou et al. (2023) introduce the concept of partial connectedness, which excludes the influence of specific groups to isolate the net effect between two groups. In our case, we aim to analyze how risk factors (CDS and GSCI) affect the REER and local fuel volatility. To achieve this, the authors propose a framework called partial connectedness, where the overall connectedness is separated into two components: inclusive connectedness, and exclusive connectedness.

In the same fashion as the directional measures were built, we compute $TO^{inc}i, t(H)$, $FROM^{inc}i, t(H)$, and $NET^{inc}i, t(H)$ as the inclusive total directional connectedness **to** and **from** others, and the **net** inclusive total directional connectedness. Thus, the $TCIint$ designates the inclusive total connectedness index measures of the interconnectedness between risk factors and fuel volatility, excluding the REER propagation mechanism. Similarly, the same approach is applied to the exclusive total directional connectedness with $TO^{exc}i, t(H)$, $FROM^{exc}i, t(H)$, and $NET^{exc}i, t(H)$ as the exclusive **to** and **from** others, and the **net** exclusive total directional connectedness of series i. However, the $TCI^{exc}t$ describes the exclusive total connectedness index that gauges the interconnectedness between REER and fuel volatility, excluding the relationship of the risk factors.

$$TCI_t = TCI^{inc}_t + TCI^{exc}_t$$

5 Results

5.1 Multivariate Stochastic Volatility

We start our analysis by estimating the MSV of the CDS, GSCI, REER, Ethanol, Gasoline, and Diesel log-returns. The dataset consists of $n = 236$ and $m = 6$ dimensions. To identify the factor loadings, a lower-diagonal factor loading matrix is imposed. This means that the loading factors are ordered, with the highest loading factor being 1, the second-highest being 2, and so on. It is worth mentioning that the prior distribution is specified before the estimation process.[5] Finally, an MCMC sampler is run to obtain samples from the posterior distribution of the loading factors, which allows for identifying and analyzing their distributions. Fig.2 displays the joint posterior distribution of the two-factor loadings, and the colors indicate the random scatterplot of MCMC draws. The local fuels (diesel and gasoline) and the GSCI indicate similar loadings on the underlying factors.

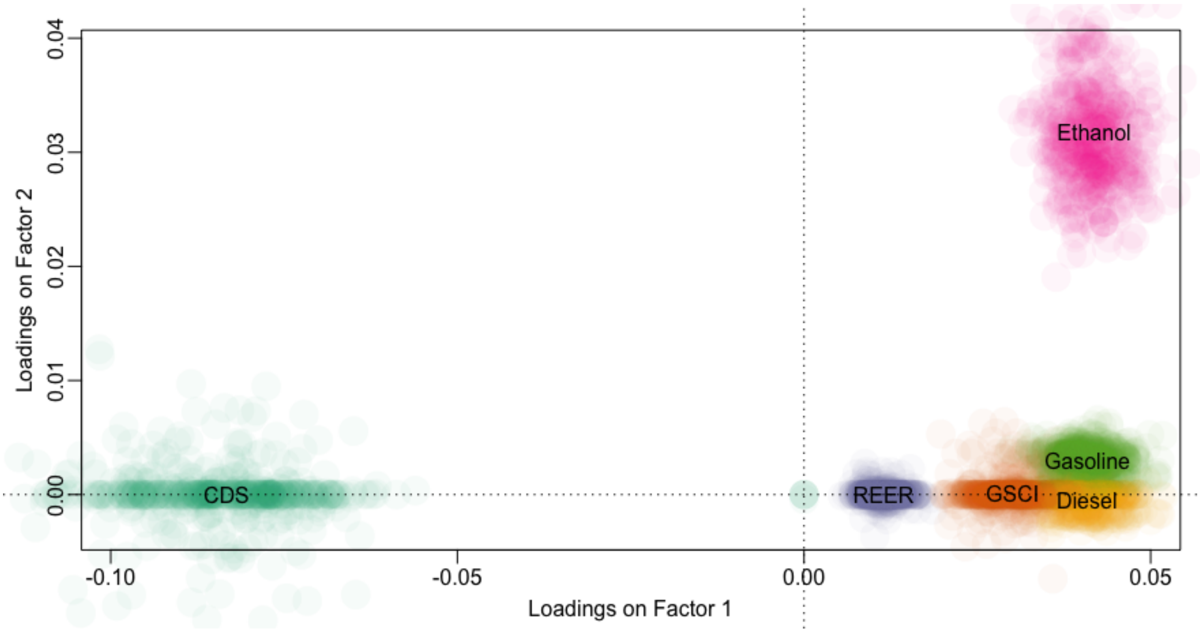


Figure 2: Factor loading of the joint posterior distribution of the 2-factor loadings for CDS, GSCI, REER, Ethanol, Gasoline, and Diesel.

We generate the marginal posterior univariate volatility for all variables in Fig.9a and the pairwise volatility between CDS, GSCI, and REER with the fuel prices in Fig. 9b. Notably, the CDS exhibits the highest volatility compared to the other variables, featuring two prominent peaks: one notably pronounced, associated with the COVID-19 outbreak in 2020, and the other around 2008 during the Subprime crisis. Figures 11a and 11b depict the posterior weekly SV before and after the implementation of the IPP, respectively. Prior to the IPP, ethanol volatility was more pronounced, whereas diesel exhibited greater volatility following the IPP.

Next, we focus our attention on the posterior correlation. Despite the main spikes observed in the marginal volatility, our study concentrates on the pricing policy of Petrobras. For in-

[5]The prior hyperparameters (b_β, B_β) is passed to a sequence of the mean and standard deviation of the normal distribution. See Kastner et al. (2017) for further details.

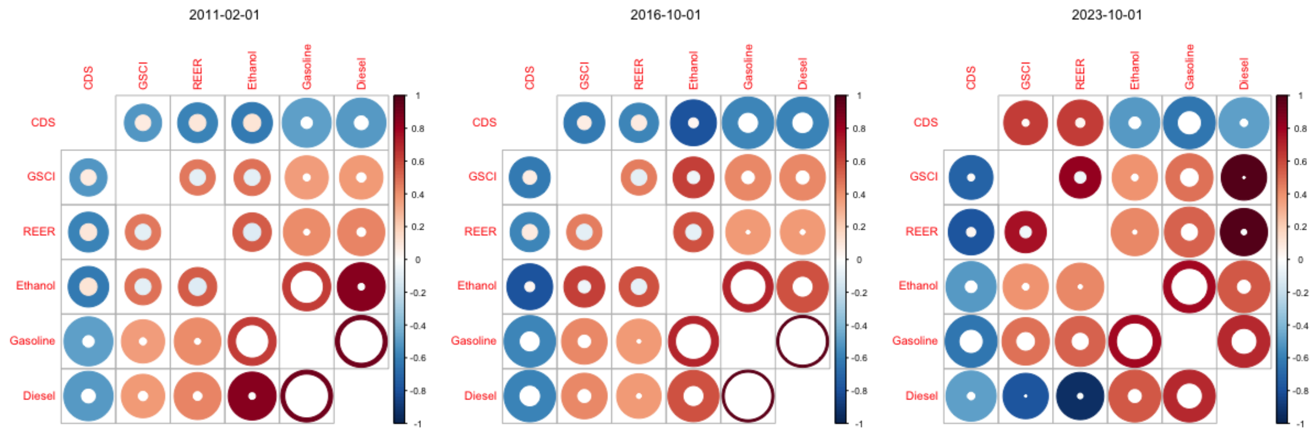


Figure 3: Posterior correlation on the initial date February 2004, followed by February 2011, October 2016, and October 2023. The circles are colored blue and red to illustrate negative and positive correlation values, respectively. The transparency of the circles depicts the posterior mean of the correlation values. The radii (inner and outer) of the circles represent the posterior mean of $-/+$ two standard deviations.

stance, we depict our correlation at given dates representing the initial date, followed by the initial phase when the government started to subsidize fuel around 2011 (Costa and Burnquist, 2016), and then the IPP in October 2016. Thus, Fig.3 depicts the posterior correlation for these periods. Each circle in the plot represents the uncertainty associated with a correlation value in the matrices. A larger circle indicates greater uncertainty in the estimation, whereas higher transparency indicates that the corresponding correlation values have a higher posterior mean. The CDS consistently exhibits a negative correlation with all variables. This pattern persists until the last plot (October 2023), when the correlation with the GSCI and REER becomes positive. The change in pattern is pronounced for the last period, while the other periods remained similar. We show in Appendix Fig.9b the posterior mean pairwise with the risk factors (CDS, GSCI, and REER).

5.2 Spillover and connectedness analysis

We commence by presenting the average connectedness results in Table 1. Our analysis encompasses both pre- and post-IPP periods. The results corresponding to the post-IPP period are enclosed in brackets. Notably, the CDS and gasoline exhibit the highest degree of connectedness within the system, serving as net transmitters of shocks at 29.11% and 31.86%, respectively. However, following the IPP implementation, the CDS experienced a notable increase in its transmission, rising to 42.28%, while diesel emerged as the second-highest contributor to volatility. These findings underscore the significant role of the CDS in propagating volatility within the system, with its contribution escalating by over 40%. Moreover, the GSCI demonstrated an amplified transmission, whereas the REER transitioned to a more pronounced net receiver status. The outcomes thus far suggest a heightened transmission of international commodities prices, rendering them increasingly pertinent within the broader system after IPP adoption. Noteworthy is the decline in gasoline's participation, yielding ground to diesel. This observation underscores the impact of the IPP policy, wherein the influence of international prices becomes more discernible post-implementation.

We subsequently examine partial connectedness, wherein we isolate the effects of the CDS and GSCI from the system (RiskFactors-REER). Notably, we observe a stronger net transmitter effect attributable to diesel before the implementation of the IPP, accounting for 11.74% of the total, in comparison to gasoline at 10.62%, given gasoline's transition to a net receiver status post-IPP (-0.04%). Furthermore, we isolate the interaction exclusively between the REER and fuel prices (REER+Fuel). Following the IPP, diesel demonstrates an increase in its net transmitter effect from 14.31% to 17.23%, while gasoline registers a decrease from 21.24% to 15.09%. Remarkably, ethanol emerges as a net transmitter when the effects of the CDS and GSCI are eliminated, highlighting its sensitivity to international shocks. Additionally, we observe that the shocks within this category appear to account for a significant portion of the REER net receiver shocks.

We shift our focus towards examining internal and external connectedness within the network. Firstly, regarding internal interactions, we observe that ethanol and diesel transitioned to net transmitters following the implementation of the IPP, whereas gasoline exhibited an inverse trajectory, declining from 1.39% to -2.11%. In terms of external shocks originating from the broader network affecting fuel prices, we discern a distinct pattern: ethanol transitions from being a net transmitter to a receiver, while both gasoline and diesel exhibit a reduction in their transmission. These effects underscore the notion that post-IPP, fuel volatility becomes increasingly influenced by external factors, while the REER assumes a more prominent role as a receiver of volatility. In Appendix B, Figure 12 illustrates the interaction among the variables within our network. The arrows denote both the strength and direction of connectedness.

Finally, we analyze the net directional connectedness depicted in Fig. 4. The pink line refers to inclusive NET dynamic connectedness between risk factor shocks and the rest of the network, while the green line captures net dynamic connectedness excluding the risk factors. The CDS is the highest net transmitter of volatility and the REER is the highest net receiver. Notably, during the sub-prime crisis, the shock deriving from the risk factors becomes a net transmitter, while the effect excluding the risk factors goes in the opposite direction.

Overall, we observe the significant role of the CDS throughout the entire system over time. Diesel emerged as the primary fuel that intensified its transmission. Conversely, gasoline exhibited a contrasting trend, experiencing a decrease in its influence and ultimately transitioning to a net receiver by the conclusion of our sample period. These findings underscore the impacts of the pricing policies implemented by Petrobras. Specifically, in March 2015, the ethanol blend in gasoline was increased from 22% to 27%. Subsequently, Petrobras initiated a series of fuel price hikes, notably in 2017 when the company began adjusting prices more frequently, even on a daily basis. These actions led to tensions among truck drivers, culminating in a nationwide strike in May 2018. Given the paramount importance of the road system in Brazil, the president acquiesced to pressure and opted to reduce diesel prices. Consequently, we observed an increase in diesel transmission during this period, juxtaposed with a reduction in gasoline transmission. Furthermore, our analysis reveals the discernible impact of gasoline's inclusive effect on the overall total net connectedness, contrasting with its lesser effect on the REER following the implementation of the IPP, particularly when compared to diesel volatility.

Table 1: The dynamic connectedness average results

	CDS	**GSCI**	**REER**	**Ethanol**	**Gasoline**	**Diesel**
CDS	48.33	4.11	5.24	15.64	11.64	15.04
	(46.15)	(6.10)	(3.88)	(14.64)	(12.56)	(16.67)
GSCI	15.75	21.28	8.84	9.14	23.73	21.26
	(19.20)	(27.31)	(7.91)	(5.93)	(18.76)	(20.89)
REER	14.51	11.08	18.90	12.88	23.37	19.25
	(14.96)	(15.30)	(21.98)	(7.99)	(20.40)	(19.37)
Ethanol	20.30	8.26	8.84	43.48	9.81	9.32
	(24.25)	(4.83)	(4.48)	(46.78)	(10.53)	(9.13)
Gasoline	14.74	10.02	3.52	9.85	34.85	27.03
	(18.30)	(13.15)	(3.25)	(10.93)	(30.11)	(24.26)
Diesel	15.48	9.09	4.01	8.82	28.47	34.14
	(19.41)	(11.43)	(3.79)	(9.19)	(22.52)	(33.66)
TO	80.78	42.56	30.44	56.32	97.02	91.91
	(96.13)	(50.81)	(23.30)	(48.68)	(84.77)	(90.33)
NET	29.11	-36.16	-50.66	-0.20	31.86	26.05
	(42.28)	(-21.89)	(-54.72)	(-4.54)	(14.88)	(23.99)
$Net_{RiskFactors}$	11.64	-11.64				
	(13.06)	(-13.06)				
Net_{REER}			0.00			
			(0.00)			
$Net_{FuelPrices}$				-0.45	1.39	-0.94
				(0.47)	(-2.11)	(1.64)
$Net_{External}$	17.47	-24.52	-50.66	0.25	30.47	26.99
	(29.06)	(-8.83)	(-54.62)	(-5.06)	(17.15)	(22.30)
$Net_{RiskFactors-REER}$	29.11	-36.16	-11.52	-3.79	10.62	11.74
	(42.12)	(-21.89)	(-18.37)	(-8.54)	(-0.04)	(6.71)
$Net_{REER+Fuel}$			-39.14	3.59	21.24	14.31
			(-36.26)	(3.94)	(15.09)	(17.23)

5.3 Dynamic structure VAR analysis

To examine the effects of the Country Risk (CR) premium on the exchange rate (see Eq.12), we utilize the SVAR framework and compare both periods, before and after the implementation of the IPP. We construct a reduced-form Vector Autoregression (VAR) model on a monthly basis, imposing a shock to each variable in the system and allowing it to affect itself and other variables. Here, $z_t = (\Delta CR, \Delta REER, \Delta diff)$, where Δ represents the percent change. Thus, we

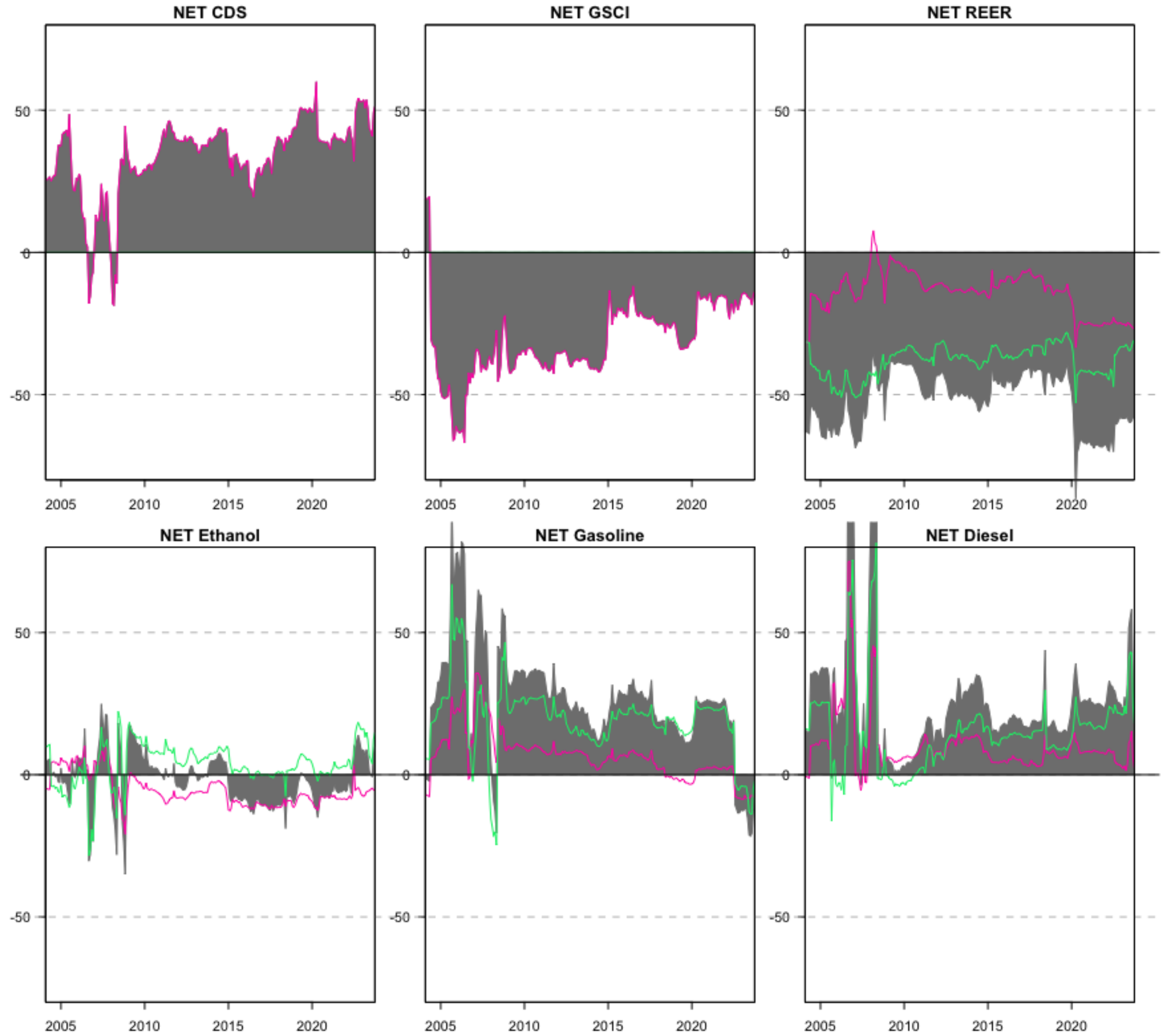


Figure 4: Net spillover effects. The grey area illustrates the net total directional, and the pink and green lines represent the inclusive and exclusive net total directional connectedness measures, respectively.

express the SVAR model as follows, following the approach outlined by (Kilian, 2009):

$$A_0 z_t = \alpha + \sum_{i=1}^{n} +A_i z_{t-i} + \varepsilon_t \tag{23}$$

The vector ε_t represents the series of serially and mutually uncorrelated structural innovations. The lag length is determined by the Akaike information criteria (AIC), with the maximum lag length set to 12.

The impact of the Country Risk (CR) premium on the Real Effective Exchange Rate (REER) and the interest rate differential before and after the implementation of the IPP is not statistically significant, as illustrated in Figure 5. However, a shock to the REER on country risk exhibits a fast-dying negative impact, with this effect becoming more pronounced after the IPP (with a baseline change of -10%). In Figure 6, we introduce the Global Commodity Price Index (GSCI) to elucidate its impact on country risk and the interest rate differential. Similar to Figure 5, the observed pattern remains consistent, albeit with a more pronounced effect after the IPP. Notably, the impact of a GSCI shock on the REER appears to intensify after the first month before quickly reversing.

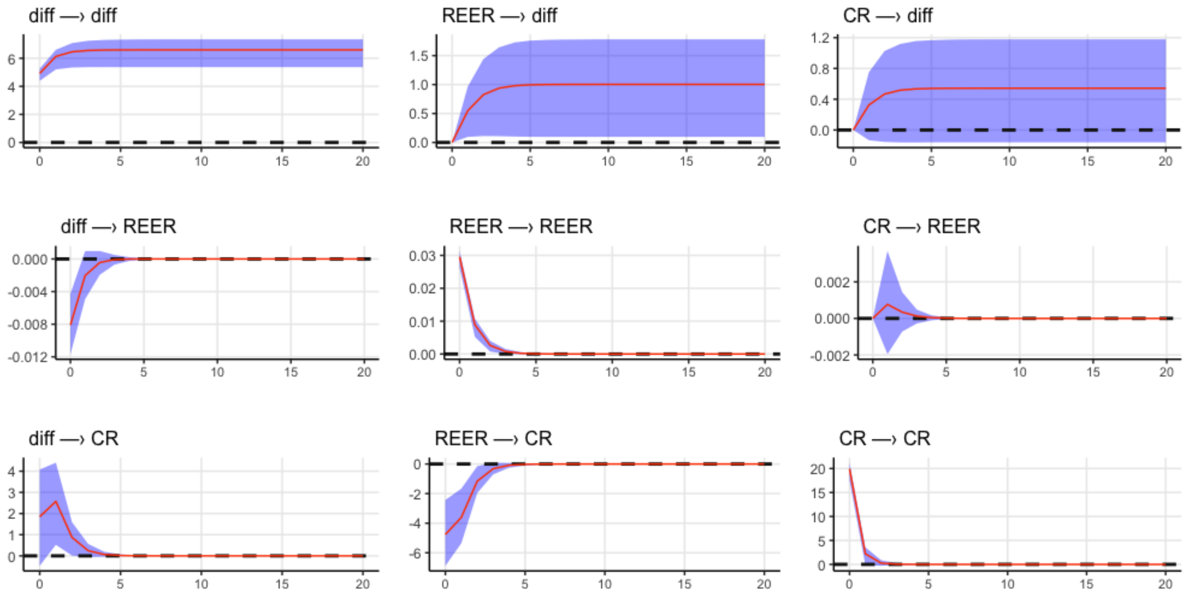
Our initial framework predicted a specific effect of country risk premium shocks on the REER. However, this effect was not observed in the data. When we expanded the analysis to include CDS spreads, a shock to the CDS led to a significant decrease in the REER starting from the first month and persisting throughout the entire period. Interestingly, this effect became even stronger after the implementation of the IPP.

In summary, the REER displayed a heightened sensitivity to market factors following the IPP. This sensitivity was evident in both the response to the GSCI and the CDS. Additionally, our composite cr index based on the 'cupom cambial' appeared to be more reactive to changes, while the CDS emerged as a more accurate measure of country risk. This suggests that market participants might react more swiftly to CDS changes than to CR approach, potentially influencing the REER more directly. The initial positive response of the interest rate differential to a CDS shock aligns with our framework. However, this effect reversed after a few months. This suggests the presence of other factors influencing the REER. Potential explanations include foreign exchange intervention by the Central Bank (NEDELJKOVIC and SABOROWSKI, 2019; Kohlscheen and Andrade, 2014) and government efforts to adjust fuel subsidies to mitigate inflation, which could also impact the REER.

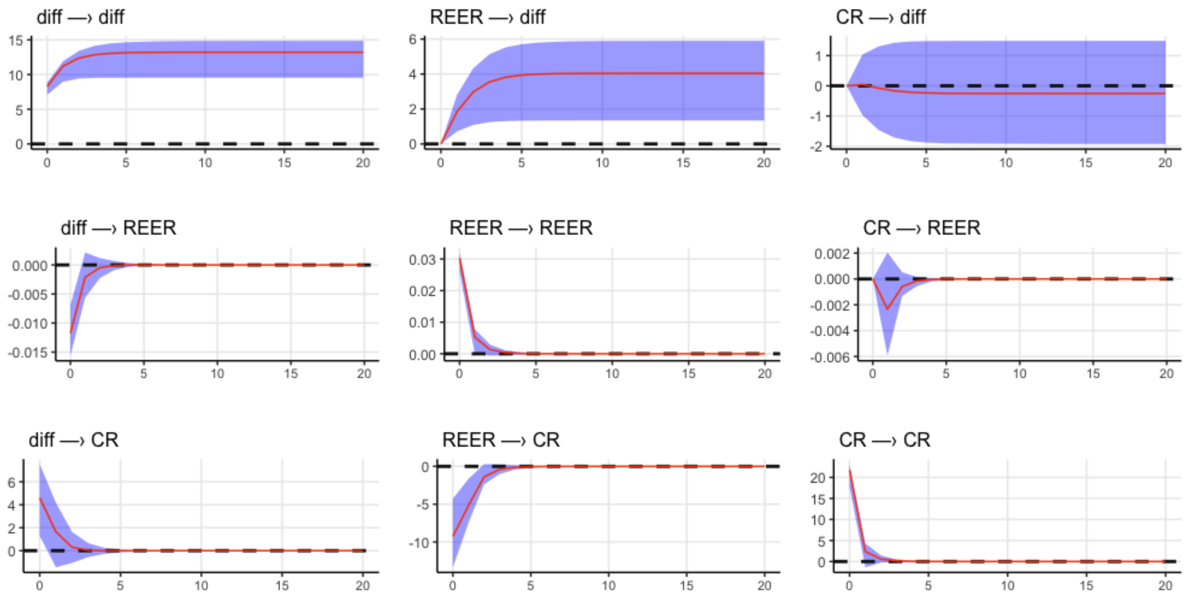
5.4 Robustness analysis - Markov switching analysis

In the preceding section, we examined the posterior SV of all variables, observing an increase in diesel volatility and a significant reduction in ethanol volatility. To ensure thorough consideration of this analysis, we expand our investigation by examining the volatility regime between these periods (before and after IPP). To achieve this, we adopt the approach proposed by Haas et al. (2004). The authors introduced a novel method for the Markov-switching model, which models an independent switching GARCH process with a skewed conditional mixture density. We follow the Ardia et al. (2019) implementation.

We start by choosing the best conditional volatility model that minimizes the BIC as well as the

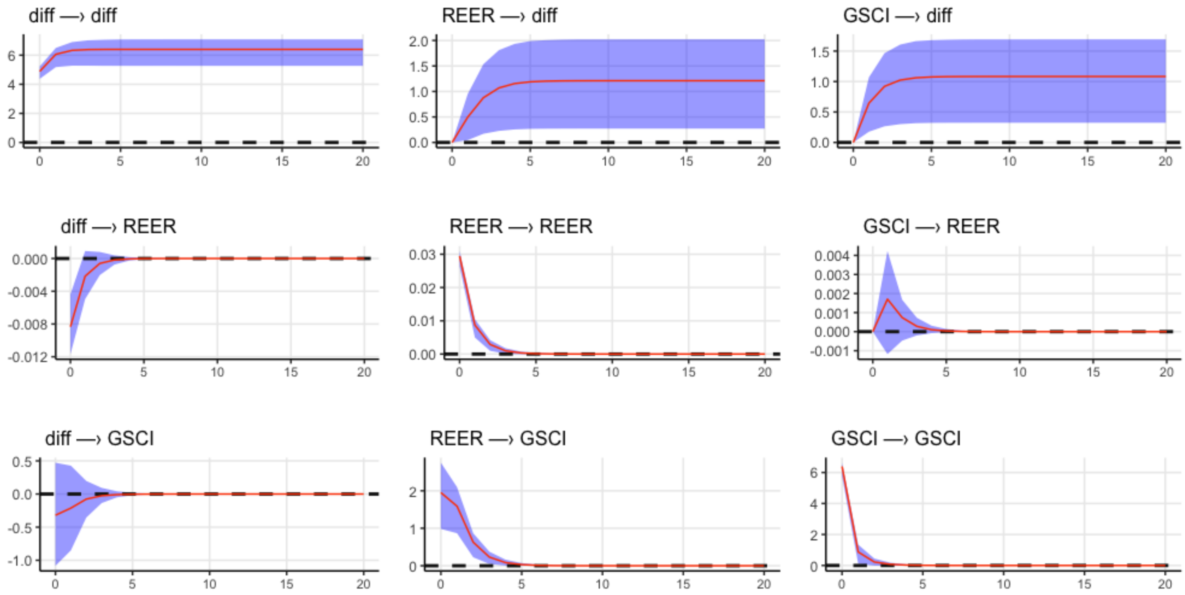


(a) Prior IPP.

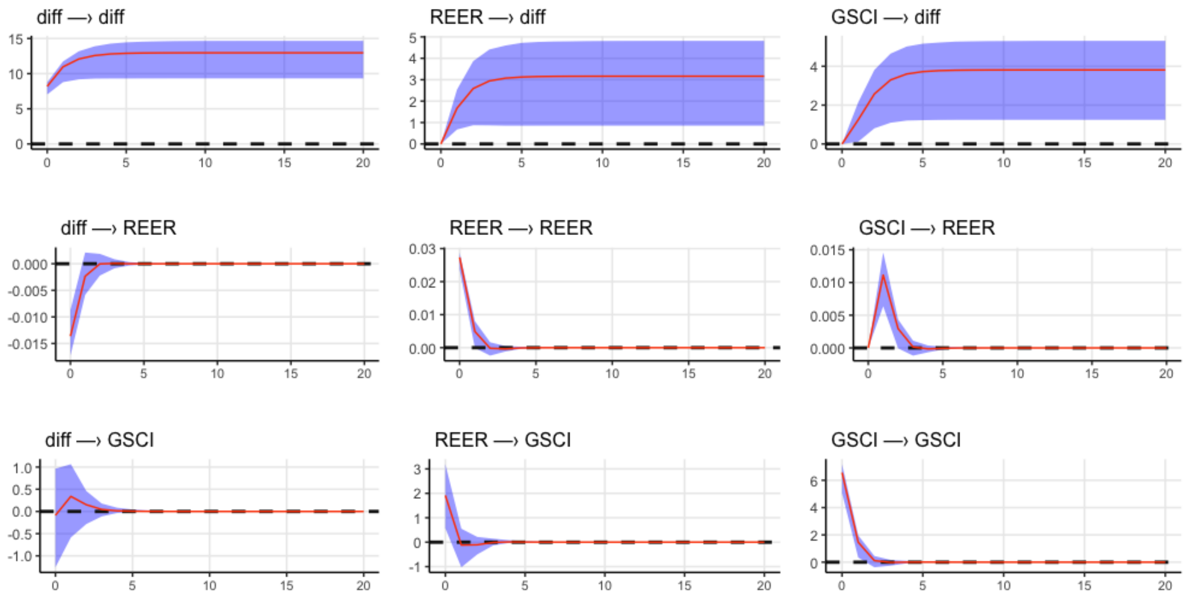


(b) Post IPP

Figure 5: The structural impulse responses of the variables REER, CR, and diff on themselves before (a) and after (b) the IPP.

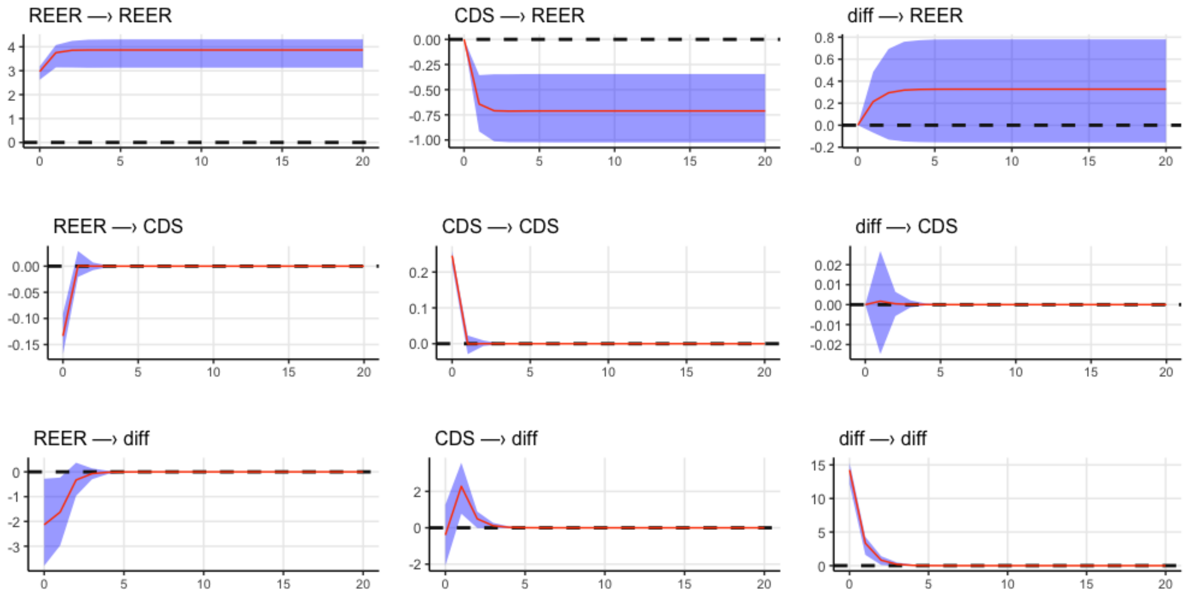


(a) Prior IPP.

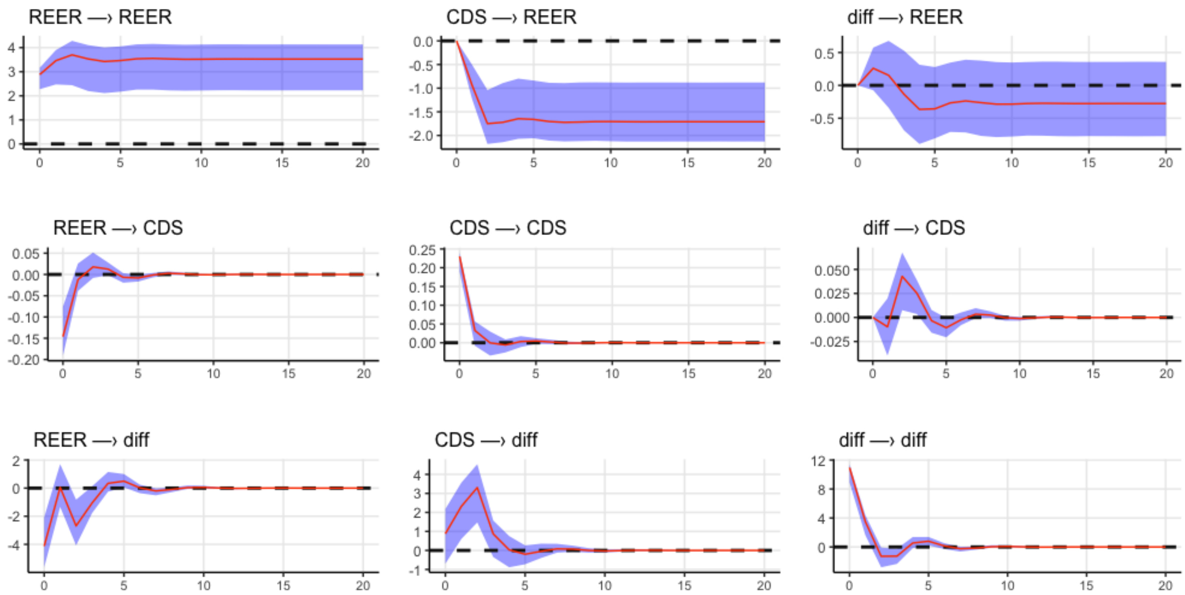


(b) Post IPP.

Figure 6: The structural impulse responses of the variables REER, GSCI, and diff on themselves before (a) and after (b) the IPP.



(a) Prior IPP.



(b) Post IPP

Figure 7: The structural impulse responses of the variables REER, CDS, and diff on themselves before (a) and after (b) the IPP.

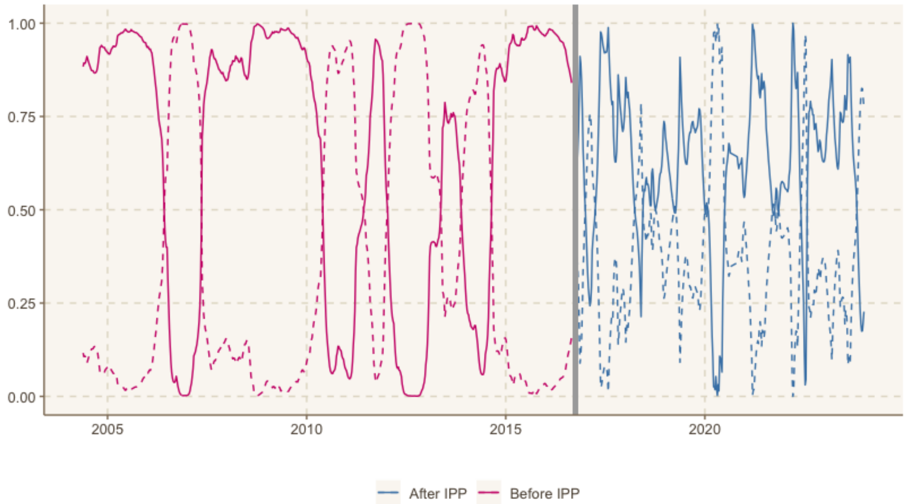
conditional distributions. We, then, set 2 regimes— low and high volatility regimes ($k = 1$ and $k = 2$, respectively)— that assume that returns are normally distributed with GARCH(1,1) for both Markov chain regimes. We employ the Maximum Likelihood procedure to fit the model. Fig. 8c shows the volatility regime for ethanol. We can see that after the IPP the volatility smoothed, while the gasoline volatility increased after the IPP. Hence, these results demonstrate that despite the increase in gasoline volatility after IPP, the ethanol volatility smoothened, while persistence in the diesel volatility seemed more pronounced after the IPP. In Appendix A.1, Figure 11 illustrates the smoothed probability for the Brazilian exchange rate and the Value at Risk (VaR) at the 5% level, along with its violations.

6 Conclusion and policy implications

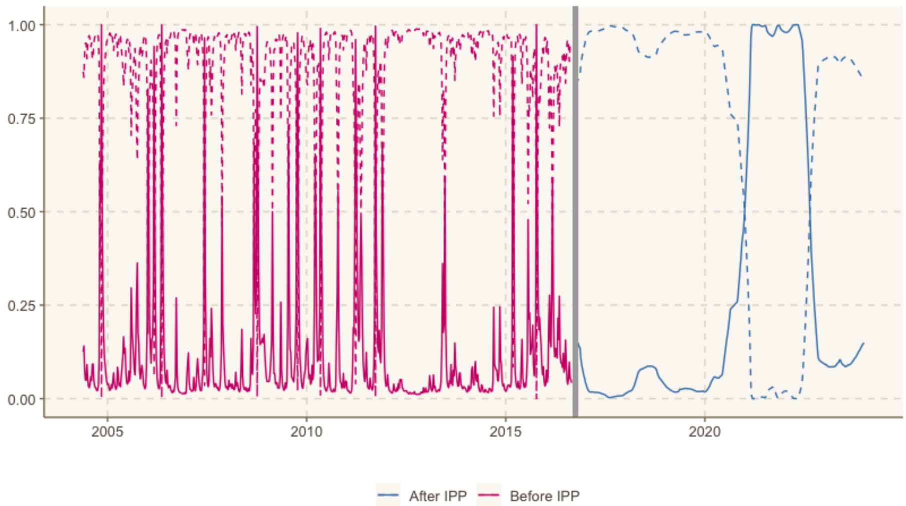
This study explores the dynamics of volatility spillover effects among fuel prices in Brazil, the country's risk premium, the commodity index (GSCI), and the Real Effective Exchange Rate (REER) before and after the implementation of the Import Price Parity (IPP) by the Petrobras president. Our findings shed light on the IPP transition, wherein international price volatility and the contribution of Credit Default Swaps (CDS) to REER volatility intensified post-IPP. Notably, ethanol volatility witnessed a significant decrease post-IPP, whereas gasoline exhibited only a partial decline. Moreover, diesel volatility exhibited sporadic spikes, particularly around 2018 and 2023.

A caveat worth mentioning is that this study does not intend to evaluate the price policy; rather, it presents a comprehensive analysis of the spillover effects of the risk factors on fuel prices in Brazil and how these shocks affect the REER. Overall, volatility became more sensitive to external factors such as commodity shocks and the country's risk premium. Nonetheless, the energy matrix increased its ethanol participation and reduced the influence of gasoline. This trend is evident when considering the drop in subsidies to petroleum after the IPP, indicating an improved energy transition towards green energy in the country. Despite the price policy becoming more adherent to international prices, several instances of government intervention, especially with diesel, were observed. Thus, the termination of the IPP raises questions about the future dynamics of volatility in Brazil.

(a) Diesel MS-GARCH before IPP and after IPP policy.



(b) Gasoline MS-GARCH before IPP and after IPP policy.



(c) Ethanol MS-GARCH before IPP and after IPP policy.

Figure 8: Plots (a), (b), and (c) depict the Markov-switching regime transition, where the dashed line represents Regime 1, and the solid line represents Regime 2, low and high volatility regimes, respectively.

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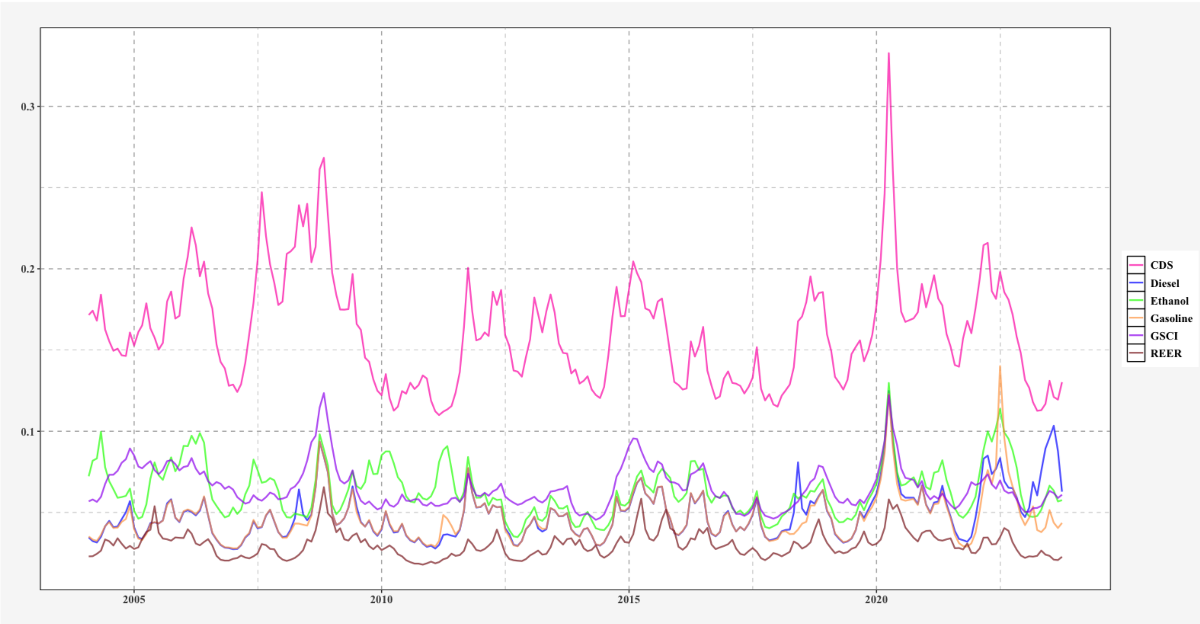
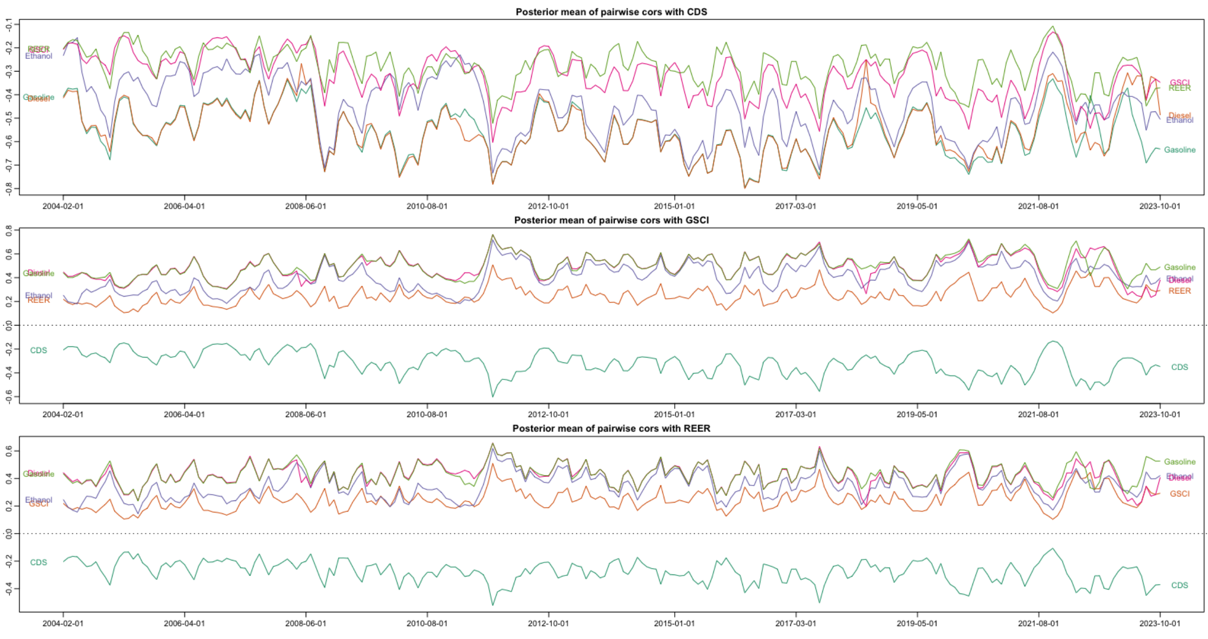
Appendix A.1: MSV analysis

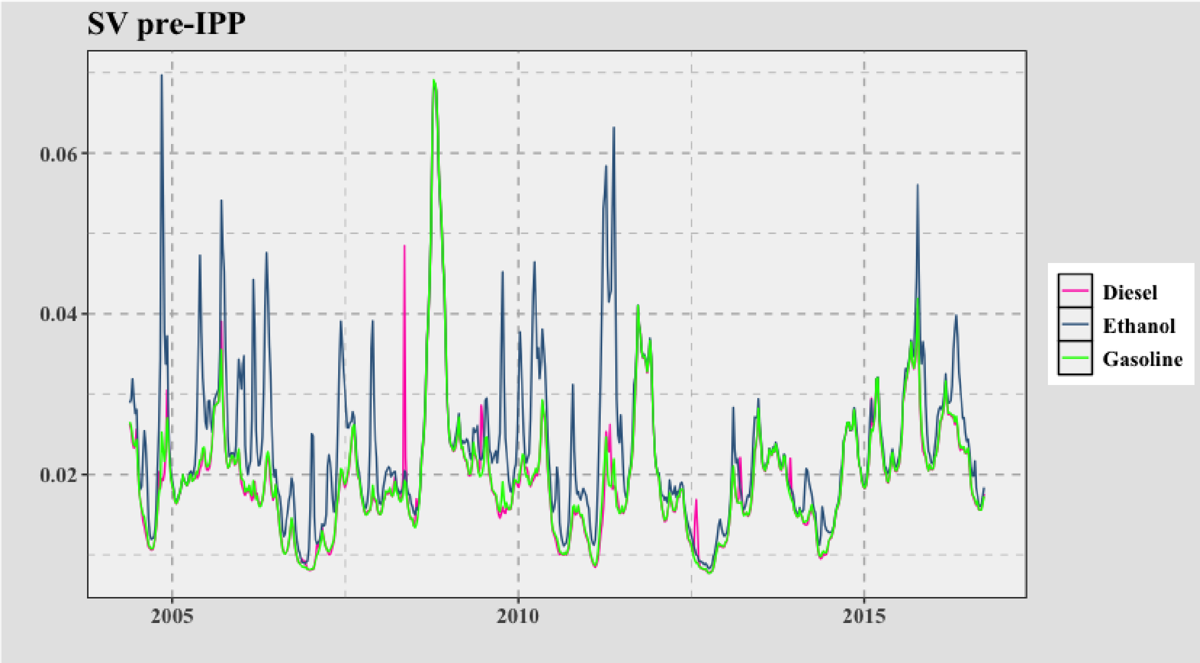


(a) Posterior monthly marginal volatility of the CDS, GSCI, REER, Ethanol, Gasoline, and Diesel.

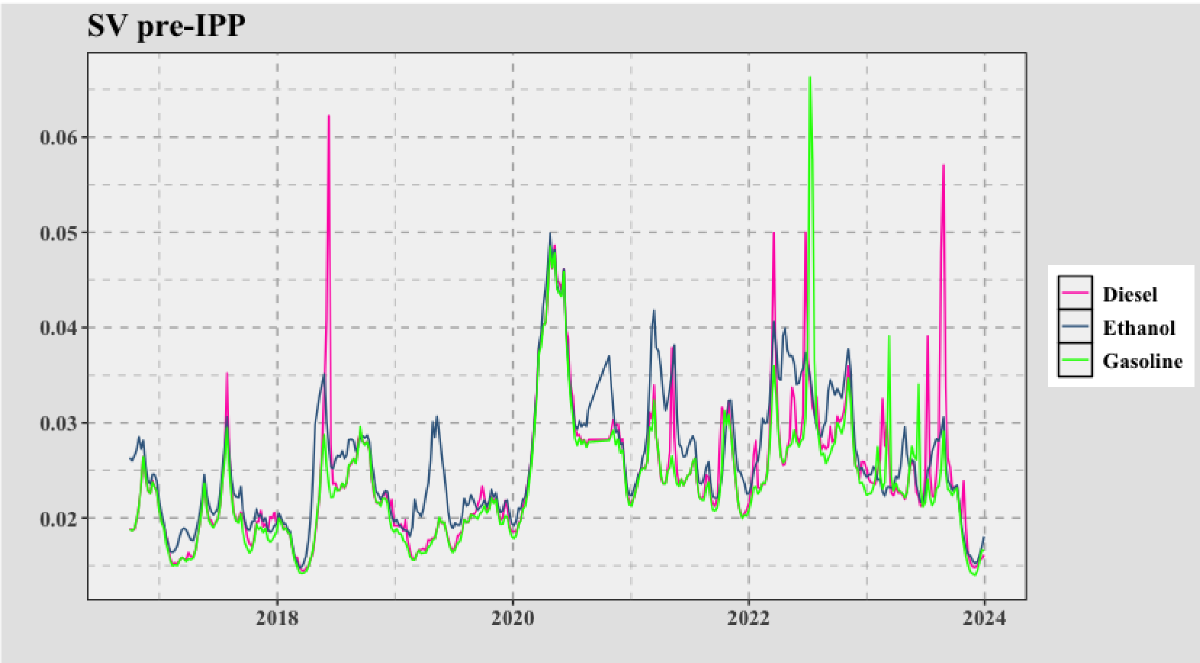


(b) Posterior mean pairwise mean with CDS, GSCI, and REER.

Figure 9: Posterior analysis



(a) Posterior weekly marginal volatility of the Ethanol, Gasoline, and Diesel pre-IPP policy.



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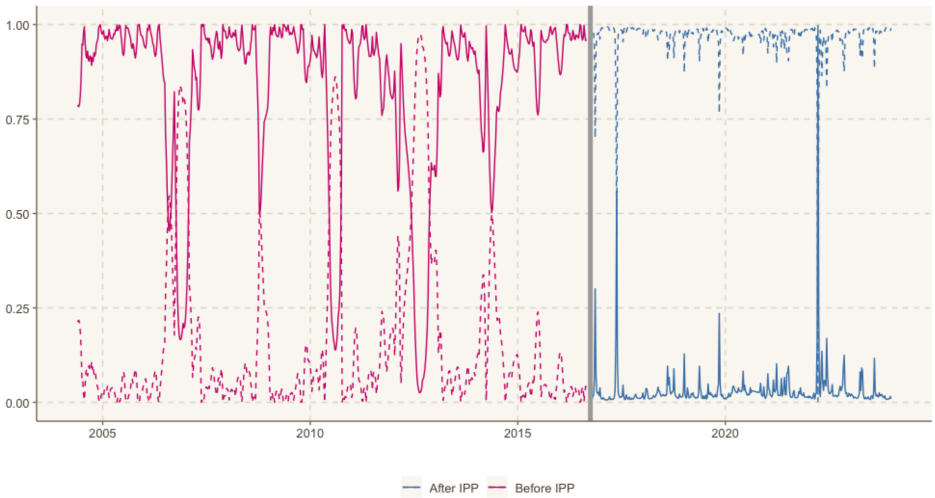
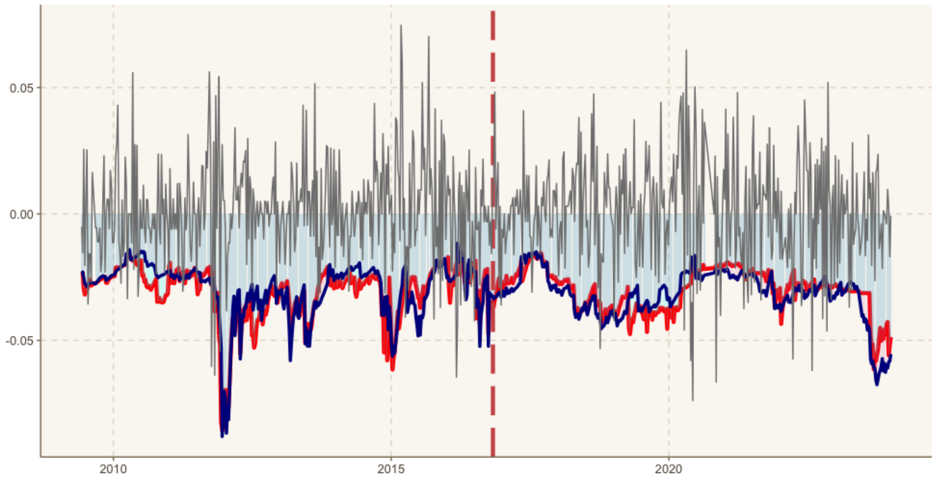
(b) Posterior weekly marginal volatility of the Ethanol, Gasoline, and Diesel post-IPP policy.

Figure 10: Posterior analysis

Appendix A.2: MSGARCH nominal exchange rate (BRL)



(a) The smoothed probabilities estimated, using the MSGARCH two-regime skewed Student (std) GJR model for the weekly nominal Brazilian exchange rate



(b) The one-day ahead Value at Risk (VaR) forecasts at the 5% risk level of the GARCH-type model is represented by the blue line and the single-regime is depicted by the red line. The gray line corresponds to the log-returns of the weekly Brazilian exchange rate. The vertical dashed line indicates the boundary between the periods before and after the implementation of the IPP.

Figure 11: Volatility analysis of the weekly Brazilian FX rate.

Appendix B: Network analysis

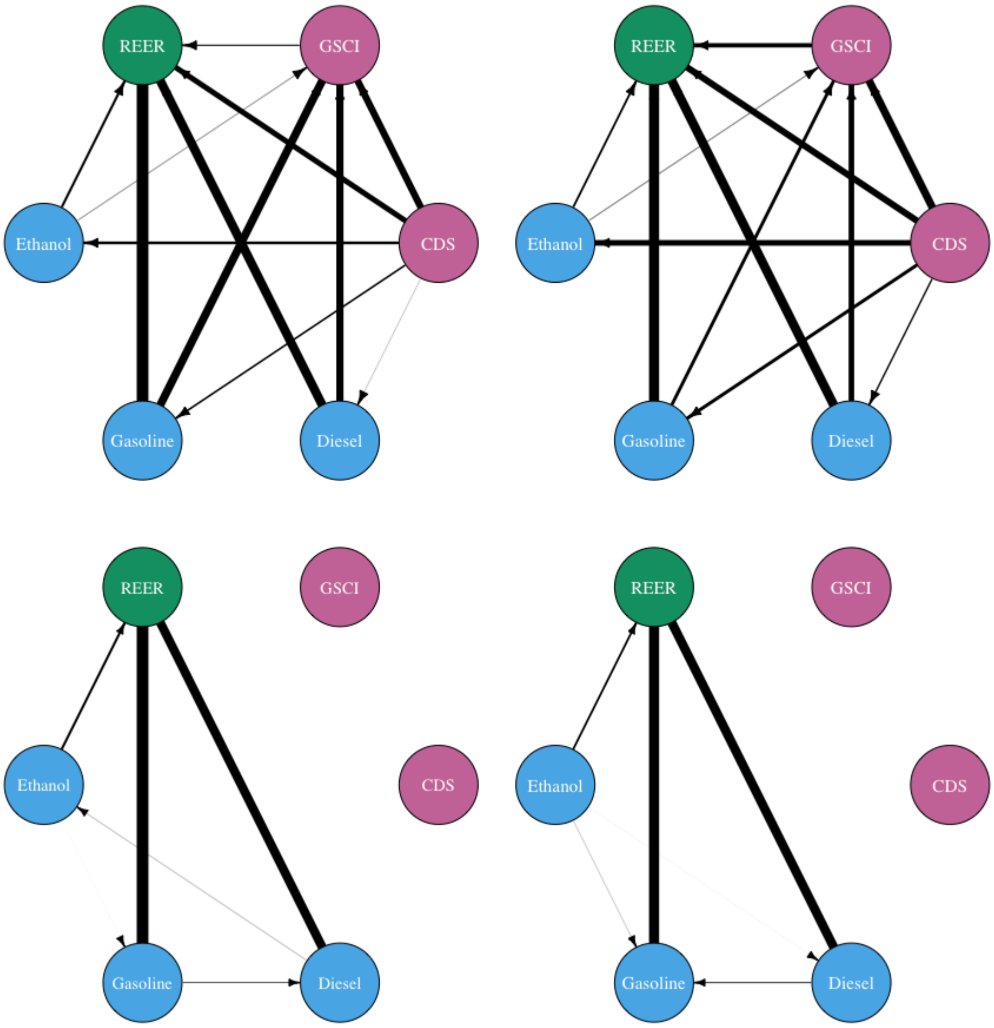


Figure 12: Net pairwise directional of the GSCI volatility in pink, the REER volatility in green, and the fuel volatility prices in blue, before IPP and after IPP policy.