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Instituto de Economia e Relações Internacionais – Universidade Federal de Uberlândia

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Asymmetric Analysis of Brazil-China and Brazil-US Bilateral Trade Flows

Uma abordagem assimétrica sobre o fluxo comercial bilateral Brasil-China e Brasil-EUA

Danilo Luciano Pires [a]
Claudio Roberto Fóffano Vasconcelos [b]

Abstract: This study investigates the asymmetric impacts of real bilateral exchange rate volatility on Brazil's export and import flows. The analysis focuses on Brazil's trade with the United States and China, disaggregated by two-digit industry classifications (99 sectors), covering the period from 2000 to 2017. The main findings reveal asymmetries in both exports and imports: 12.12% and 9.09%, respectively, in Brazil–US trade; and 10.10% and 8.08%, respectively, in Brazil–China trade.

Keywords: Volatility, Asymmetry, Exchange rate, trade flows, NARDL.
JEL Classification: F10; F14; F31

Resumo: O propósito do estudo é investigar os impactos assimétricos na volatilidade da taxa de câmbio real bilateral em relação aos outputs do fluxo de exportação e importação da economia brasileira. Essa análise destina-se aos EUA e a China para os setores desagregados a dois dígitos da economia brasileira (99 indústrias) no período de 2000 a 2017. Os principais resultados atestam assimetria nas exportações e importações, Brasil-EUA na ordem de 12,12% e 9,09% respectivamente. O caso Brasil-China para exportação e importação verificaram-se resultados na ordem de 10,10% e 8,08% respectivamente.

Palavra-chave: Volatilidade, Assimetria, Taxa de câmbio, fluxo comercial, *NARDL*.
Classificação JEL: F10; F14; F31

[a] Danilo Pires. Ph.D. in Economics. Visiting Professor, Department of Economics, Federal University of Juiz de Fora (UFJF), Brazil. E-mail: danilopiresufjf@gmail.com; danilo.pires@ufjf.br
ORCID: https://orcid.org/0009-0009-4241-4352

[b] Claudio Vasconcelos. Ph.D. in Economics. Full Professor, Faculty of Economics, Federal University of Juiz de Fora (UFJF), Brazil. E-mail: claudio.foffano@ufjf.br
ORCID: https://orcid.org/0000-0003-4947-9895

1. Introduction

The collapse of the Bretton Woods system marked the beginning of a new era in the history of international trade, specifically the transition from a fixed exchange rate regime to a floating exchange rate regime. This shift introduced unprecedented concerns—particularly regarding real exchange rate volatility. As a result of the adoption of floating exchange rates, global trade became increasingly exposed to currency instability, which introduced significant risks to international trade flows, including heightened exchange rate uncertainty.

Traditionally, studies examining trade flows and exchange rate fluctuations rely on symmetric analyses, as documented by several authors (BAHMANI-OSKOOEE, 1991; BAHMANI-OSKOOEE and PAYESTEH, 1993; DOROODIAN, 1999; BAHMANI-OSKOOEE, 2002; and BAHMANI-OSKOOEE and AFTAB, 2017). Before addressing the relevance of asymmetric effects in this context, it is important to clarify the basic distinction between the terms "symmetric" and "asymmetric." Asymmetry, by definition, is understood through contrast—it refers to the absence or opposite of symmetry, which implies the property of being divisible into parts that perfectly match when mirrored or overlapped.

Symmetry in trade flow and exchange rate fluctuations refers to whether firms, whether they are exporters or importers, respond proportionally to exchange rate depreciation or appreciation. Traditional linear regression models do not fully capture the true trade effects that should be considered. Symmetric models incompletely capture the separate and distinct effects of rising and falling exchange rate volatility on trade flows. This means that a national firm could export or import a certain product based on a univocal perception of an exchange rate appreciation or depreciation, depending on whether it is rising or falling over time (BAHMANI-OSKOOEE and AFTAB 2017).

Observing the limitations of the symmetric mechanism, Bahmani-Oskooee and Aftab (2017) and Itodo et al. (2017) propose a hypothesis regarding exchange rate fluctuations and trade flows from a nonlinear and asymmetric perspective. The nonlinear and asymmetric approach allows capturing, within the same regression, the dual impacts of exchange rate volatility on trade flows. In other words, it implies that economic agents' perceptions (exporters or importers) differ depending on whether exchange rate volatility increases or decreases over time, in the context of currency appreciation or depreciation. Furthermore, the intuition of asymmetric models is that economic agents' expectations fluctuate when, for example, a currency depreciates versus when it appreciates. This means that when firms are importing or exporting a certain product, they respond differently to exchange rate fluctuations. Therefore, asymmetric models perform differently when the exchange rate volatility increases or decreases over time.

Economic agents are not expected to respond symmetrically to fluctuations in exchange rate volatility during episodes of currency appreciation and depreciation. When firms form expectations and revise their strategic outlook, such adjustments may reflect the way exchange rate shocks are perceived—potentially responding more strongly to depreciation than to appreciation. This perception bias may shape trade decisions differently depending on the direction of the exchange rate movement. Accordingly, this study aims to validate the hypothesis that traded goods between Brazil and its two major trading partners (China and the United States) are influenced by asymmetric effects of real bilateral exchange rate volatility on international trade flows.

One of the key challenges for future research on this topic lies in interpreting the parameters of asymmetric models, should asymmetry be confirmed according to the technical specifications of a given econometric framework. After highlighting the relevance of asymmetric models, this study investigates the nuances—through an asymmetric lens—of Brazil’s export and import flows with the United States (US) and China in relation to exchange rate volatility, covering the period from 2000 to 2017. The analysis is conducted at the two-digit level of the Harmonized System (HS), encompassing 99 industries. The time frame was selected based on the availability and consistency of the dataset, as it allows for the construction of the most comprehensive time series for US and Chinese trade flows with Brazil. Moreover, the study deliberately excludes the COVID-19 outbreak, since the first confirmed case was reported in China on November 17, 2019.

This study offers a meaningful contribution to the literature on international economics and trade flows. In line with Bahmani-Oskooee and Aftab (2017), it applies econometric procedures to the Brazilian economy and its two major trading partners—China and the United States—as previously explored by the aforementioned authors. However, this research goes a step further by conducting a detailed examination of asymmetric parameters, aiming to generate insights of practical relevance for policymakers, particularly in sectors tied to commodities and manufactured goods within the Brazilian economy.

Thus, given the asymmetric behavior of the appreciation and depreciation of the bilateral real exchange rate variable, there is also an asymmetric behavior of exchange rate volatility and trade flow. The objective of this study is to investigate the parameters that compute asymmetry, specifically the asymmetric impacts caused by positive and negative exchange rate volatility inputs in relation to Brazil's export and import flow outputs to its two largest world trade partners, China and the US. The study's econometric feasibility is based on the cointegration approach of the Nonlinear Autoregressive Distributed Lag (NARDL) model proposed by Shin *et al*. (2014). The study constructs the bilateral real exchange rate volatility variable using the Generalized Autoregressive Conditional Heteroskedasticity model—GARCH(1,1)—proposed by Bollerslev (1986). The paper is divided into the following sections: (1) introduction, (2) theoretical framework, (3) methodology and data analysis, (4) results, and (5) conclusion.

2. Empirical literature review

In the 21st century, studies investigating the influence of exchange rate volatility on trade flows toward emerging countries have stood out. For example, Bahmani-Oskooee and Harvey (2011) used disaggregated products to analyze trade flows through exports and imports between the US and Malaysia. The authors employed the autoregressive distributed lag (ARDL) technique. The study essentially consisted of two distinct phases. Initially, they examined the products in aggregate and found no significant results in the short run or long run. Subsequently, the disaggregated approach allowed the analysis of 101 US exporting industries to Malaysia and 17 Malaysian importing industries from the US. Consequently, the study identified significance in approximately two-thirds of industries in the short run and one-third in the long run. However, even with commodity-level disaggregation, import results were significant for only one-third of the industries. This indicates no evidence that exchange rate volatility impacts bilateral trade flows in the case of imports.

Regarding the issue of nonlinearity in economic variables, contemporary econometric models have pointed to the ARDL metric. The latest version of this metric, disseminated by Shin *et al*. (2014), employs the Nonlinear Autoregressive Distributive Lag (NARDL). Bahmani-Oskooee and Aftab (2017) recently investigated the asymmetric effects on exchange rate volatility and trade flow using this metric. These nonlinear and asymmetric effects can occur due to changes in agents' expectations. For instance, when a currency depreciates, the effects may differ from when the same currency appreciates. The authors analyzed monthly data from 54 Malaysian industries that export to the US and 63 Malaysian industries that import from the US. The study found that exchange rate volatility resulted in asymmetric trade flow responses in approximately one-third of the industries investigated, both in the short run and the long run. This means that the industries' trade flows responded differently to upward and downward volatility

Bahmani-Oskooee and Arize (2020) conducted an analysis of the impact of exchange rate uncertainty on trade flows for 13 African countries. The study investigated the symmetric (ARDL) and asymmetric (NARDL) model for the period between 1973 and 2015, based on the trade, exports, and imports of each African country and the rest of the world. It should be noted that the impact of exchange rate volatility on export flows is country-specific. In general, the results indicated greater representativeness for the asymmetric model (NARDL) in the long run in relation to the flow of exports (10/13 cases identified) and imports (8/13 cases identified) for the 13 African countries.

Arize *et al*. (2021) analyzed Thailand's quarterly exports from 1973 to 2017, highlighting the relevance of asymmetric models for emerging economies. They argue that positive and negative changes in volatility likely have different effects. Using the NARDL model, they found a long-run negative relationship between exchange rate volatility and exports, regardless of the direction of fluctuations. The symmetric model failed to capture this dynamic, supporting the view that exchange rate volatility hampers trade and affects the allocation of production across sectors. Similarly, Bahmani-Oskooee and Durmaz (2021) examined the asymmetric impact of GARCH-based real exchange rate volatility of the Turkish lira against the euro on trade flows across 62 industries at the two-digit level. They identified short-run asymmetries in 38 Turkish and 49 EU exporting industries, with around 19 industries in each showing asymmetric responses. The study highlights the usefulness of nonlinear models in distinguishing the effects of rising versus falling volatility.

Souza *et al* (2021) investigated the influence of exchange rate volatility on the flow of Brazilian exports to the US between January 1999 and February 2017. The authors employed the Pesaran frontier test within the NARDL framework. Nonlinear measures were devised to assess the impact of positive and negative shocks to the exchange rate on volatility. The primary findings demonstrated the long-run impact of exchange rate volatility on export performance. However, the models that considered nonlinear measures yielded more positive results than those that employed linear measures. The sectors most adversely affected were those dependent on foreign capital and manufactured products. Conversely, sectors not dependent on foreign capital exhibited positive effects. Bahmani-Oskooee and Arize (2022) analyzed the bilateral impact between the US and 20 countries on the African continent in symmetrical and asymmetrical modalities. The main findings of the linear version of the analysis indicated that volatility exerted a notable influence on US exports to 17 partner countries and on US imports from 12 partner countries in the short run. The short-run linear effects were sustained in the long run in 12 US export models and in 7 US import models. However, in the nonlinear version, when the increase in exchange rate volatility was separated from the decreases, the comparable figures in each case exhibited a greater magnitude.

In a recent study, Iqbal and Nosheen (2022) researched the asymmetric impact of exchange rate volatility on bilateral trade flows between Pakistan and the US. The study employed disaggregated data for 48 importing industries and 23 exporting industries over the period from 1981 to 2018. The primary findings indicated a predominant short-run adjustment asymmetry in comparison to long-run asymmetric effects, with a smaller number of importing industries exhibiting sensitivity to positive and negative volatility over an extended period. In the case of exporting industries, there is substantial evidence of both short-run asymmetric effects and long-run asymmetric effects in Pakistan. The authors highlighted that the asymmetric effects are industry-specific and have implications for other industries in foreign countries. Bahmani-Oskooee *et al*. (2023) conducted an analysis of the response of trade flows in relation to the measure of exchange rate volatility in symmetric and asymmetric modalities from annual data from 1980 to 2018. The authors examined the bilateral relationship between Pakistan and its primary trading partner, China, with a focus on 14 export industries and 34 import industries. The primary findings indicate that, in the short run, nearly all industries exhibited asymmetry, while in the long run, the asymmetric effects ranged from 40% to 50% across the investigated industries for both exports and imports. The asymmetric model proved to be a more representative model than the symmetric model.

Khalid *et al*. (2023) empirically examined the asymmetric effects of exchange rate uncertainty and the effect of third countries on bilateral trade between Turkey and Germany. The time series data covers the annual period 1980-2022 for 79 industries in both export and import modalities. The authors recommend that policymakers prioritize export-oriented trade policies to boost foreign trade with other countries, rather than engaging in short-run manipulation of the national currency. A recent study by Handoyo *et al*. (2023) examined the impact of exchange rate volatility on manufactured exports within the

ASEAN-5. To ascertain the symmetric and asymmetric impact of exchange rate volatility on manufactured exports in both the short and long run, the authors employed ARCH/GARCH, ARDL, and Nonlinear ARDL models. The analysis spanned from January 2007 to March 2019. The primary findings of the study indicate that, in the ARDL model, volatility exerts a notable impact on the exports of 13 industries in the short run and 19 industries in the nonlinear ARDL version. In the long run, an asymmetric influence is evident in the majority of raw material exports under investigation. The authors posit that it is incumbent upon policymakers to maintain the stability of the exchange rate by ensuring the adequacy of foreign reserves and increasing the level of investment in the national productive sector.

Kayani *et al*. (2023) examined how asymmetric exchange rates affect trade in a group of Asian countries. The countries under consideration were Pakistan, Malaysia, Japan, and Korea. The authors employed quarterly temporal data spanning the period from 1980 to 2018. The findings revealed that both the linear (ARDL) and nonlinear (NARDL) models demonstrated the existence of short-run exchange rate volatility in exports and imports across all countries. However, in the long-run analysis, the nonlinear model demonstrated superior performance compared to the linear model. Moreover, an increase in exchange rate volatility had a detrimental effect on Pakistani exports and a beneficial effect on Japanese exports. The authors put forth the following policy recommendations: the implementation of measures to stabilize exchange rates, the enhancement of export competitiveness, the promotion of monetary stability for imports, the development of risk management strategies, and the harmonization of trade rules.

Rasaki and Oyedepo (2023) assessed the impact of exchange rate volatility on trade flows in Nigeria, utilizing quarterly data from 1995 to 2020. The results of the linear ARDL model indicate that exchange rate volatility exerts a significant short-run influence on exports and a short- and long-run impact on imports. The nonlinear NARDL model indicates that exchange rate volatility has asymmetric short- and long-run effects on imports. However, the NARDL model did not identify any asymmetric short- or long-run effects on exports. The findings indicate that the short-run effects of exchange rate volatility on imports persisted over the long run, while the short-run effects on exports did not. This indicates that exchange rate volatility exerts a more enduring influence on imports than on exports. The authors propose that the Central Bank of Nigeria (CBN) should implement exchange rate stabilization policies and periodically intervene in the foreign exchange market to mitigate the uncertainty (volatility) associated with exchange rate fluctuations, thereby fostering investor confidence.

Urgessa (2024) examined the effects of real effective exchange rate volatility on Ethiopia's export earnings, utilizing quarterly disaggregated data spanning the period from 2007 to 2021. The author compared the symmetric (ARDL) and asymmetric (NARDL) effects of exchange rate volatility for three categories of export earnings. The results of the symmetric model indicate that the real effective exchange rate and its volatility exert an influence on export earnings in select instances, particularly with regard to meat and oilseed products. In contrast, the asymmetric model demonstrated a superior fit, indicating that the volatility of the exchange rate exerted an asymmetric influence on total export revenues. Nevertheless, in the long run, there is no evidence of an asymmetric effect of exchange rate volatility on total export revenues or on the level of raw materials. The author proposes the implementation of stabilization policies with the objective of mitigating exchange rate uncertainty and thereby enhancing export earnings.

Overall, based on the studies by Bahmani-Oskooee and Aftab (2017), there is a clear trend toward specifically analyzing the effects of exchange rate volatility on international trade flows. More precisely, these studies examine sectoral trade flows (industry-level disaggregation), exchange rate volatility modeled within the ARCH/GARCH framework, bilateral trade relationships, the participation of emerging—notably—and developed countries, as well as the comparison and/or calibration between symmetric and asymmetric effects between trade flows and exchange rate volatility. That said, the present study follows the trend of the aforementioned research with two specific variations: (i) it investigates only the nonlinear asymmetric effects between trade flows and exchange rate volatility; and (ii) it conducts a detailed analysis of the separate effects of positive (rising volatility) and negative (falling volatility) shocks on the bilateral trade flows (exports and imports) between Brazil and China and between Brazil and the US. Thus, this study differs from others in this empirical review by examining the individual effects of distinct groups of positive and negative volatility on international trade flows.

3. Methodology and data analysis

According to Bahmani-Oskooee and Harvey (2011), the baseline model specification for export mode (Equation 1) and import mode (Equation 2) captures the causal relationship of bilateral trade between Brazil and the US, as well as between Brazil and China. Traded products were categorized according to two-digit codes of the Harmonized System (HS), resulting in 99 industrial sectors representative of trade. However, this study only considered sectors with trade flows equal to or exceeding 0.5% of the total volume among the 99 HS sectors. This approach allows the study to focus on sectors with the highest relative export and import volumes at the two-digit aggregation level. The standard regression model is as follows:

$$\ln \mathrm{X}_{\mathrm{i,t}} = \alpha_0 + \alpha_1 \ln \mathrm{IP}_{\mathrm{t}}^{*} + \alpha_2 \ln \mathrm{REX}_{\mathrm{t}} + \alpha_3 \ln \mathrm{V}_{\mathrm{t}} + \varepsilon_{\mathrm{t}} \tag{1}$$

$$\ln \mathrm{M}_{\mathrm{i,t}} = \beta_0 + \beta_1 \ln \mathrm{IP}_{\mathrm{t}} + \beta_2 \ln \mathrm{REX}_{\mathrm{t}} + \beta_3 \ln \mathrm{V}_{\mathrm{t}} + \mu_{\mathrm{t}} \tag{2}$$

Where: $\ln\mathrm{X}_{\mathrm{i,t}}$ is the natural logarithm (LN) of disaggregated exports of 99 Brazilian products to trading partners; $\ln\mathrm{M}_{\mathrm{i,t}}$ is the LN of disaggregated imports related to the same 99 products destined for the two main trading partners; $ln\mathrm{IP}_{\mathrm{t}}$ denotes the LN of Brazil's production index; $\ln\mathrm{IP}_{\mathrm{t}}^{*}$ denotes the LN of the production index of the two partner countries; $\mathrm{REX_t}$ corresponds to the LN of the bilateral real exchange rate between Brazil and each trading partner; and $ln\mathrm{V_t}$ represents the natural logarithm of the bilateral real exchange rate volatility. For a description and reference of the aforementioned variables, please refer to Appendix A; for details on the construction of the $\mathrm{V_t}$ variable, please see Appendix B.

Pesaran *et al*. (2001) proposed the Autoregressive Distributed Lag (ARDL) cointegration models, which introduce a dynamic adjustment mechanism for the standard model and distinguish between short- and long-run effects on the variables of interest. This metric is notable for not requiring a specification of the same order of integration in the regressors, I(0) and/or I(1). However, the model does not support an order of integration greater than one, meaning that it is not allowed or specified beyond I(2). This model is also referred to as an error correction model. To determine whether the ARDL structure is cointegrated, it is necessary to analyze the bounds test based on the non-standard F-statistic distribution. Shin *et al*. (2014) proposed the NARDL model to capture the nonlinear effects on the volatility variable of the Brazil–US and Brazil–China bilateral real exchange rate. The variable $ln\mathrm{V_t}$ was decomposed into two components: positive partial sums (POSt) and negative partial sums (NEGt).

$$POS_t = \sum_{j=1}^{I} \Delta LnV_j^{+} = \sum_{j=1}^{I} \max(\Delta LnV_j\,, 0) \tag{3}$$

$$NEG_t = \sum_{j=1}^{I} \Delta LnV_j^{-} = \sum_{j=1}^{I} \min(\Delta LnV_j\,, 0) \tag{4}$$

After decomposing $\Delta ln\mathrm{V_t}$ into ΔLnV_j^{+} and ΔLnV_j^{-}, the NARDL model is applied to the standard model for exports and imports between Brazil–US and Brazil–China.

$$\begin{aligned}\Delta LnX_{i,t} = c_1 &+ \sum_{j=1}^{n1} c_{2j}\Delta LnX_{t-j} + \sum_{j=0}^{n2} c_{3j}\Delta LnIP^{*}_{t-j} + \sum_{j=0}^{n3} c_{4j}\Delta LnREX_{t-j} \\ &+ \sum_{j=0}^{n4} c_{5j}\Delta POS_{t-j} + \sum_{j=0}^{n5} c_{6j}\Delta NEG_{t-j} + \mu_1 LnX_{t-1} + \mu_2 LnIP^{*}_{t-1} \\ &+ \mu_3 LnREX_{t-1} + \mu_4 POS_{t-1} + \mu_5 NEG_{t-1} + \varepsilon_t \end{aligned} \tag{5}$$

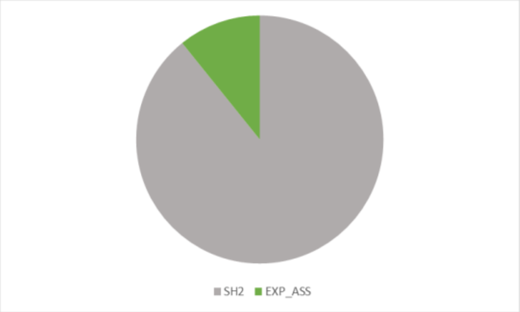
$$\Delta LnM_{i,t} = d_1 + \sum_{j=1}^{n1} d_{2j}\Delta LnM_{t-j} + \sum_{j=0}^{n2} d_{3j}\Delta LnIP_{t-j} + \sum_{j=0}^{n3} d_{4j}\Delta LnREX_{t-j} + \sum_{j=0}^{n4} d_{5j}\Delta POS_{t-j} + \sum_{j=0}^{n5} d_{6j}\Delta NEG_{t-j} + \pi_1 LnM_{t-1} + \pi_2 LnIP_{t-1} + \pi_3 LnREX_{t-1} + \pi_4 POS_{t-1} + \pi_5 NEG_{t-1} + \varepsilon_t \quad (6)$$

In the export specification (Equation 5), the short-run coefficients are c2, c3, c4, c5, and c6, while the long-run coefficients are µ1, µ2, µ3, µ4, and µ5. For the import model (Equation 6), the short-run parameters are d2, d3, d4, d5, and d6, and the long-run coefficients are π1, π2, π3, π4, and π5. Once the ARDL model has been adjusted to the NARDL framework and applied to Brazilian trade data, it becomes possible to investigate the asymmetric impacts of real bilateral exchange rate volatility on the export and import flows between Brazil and China, as well as Brazil and the US. In the case of exports, short-run coefficients c4 and c5 and long-run coefficients µ4 and µ5 will determine the direction and magnitude of the effects. The coefficients d5 and d6 in the short run and π4 and π5 in the long run will be investigated for imports.

4. Results

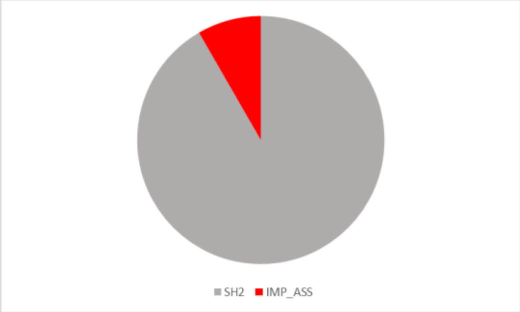
Initially, the export and import time series were tested for unit roots. Subsequently, the ARDL model's stability was assessed using LM, ARCH, CUSUM, and CUSUM-squared tests. Furthermore, cointegration among variables was evaluated through the F-bound test (see Appendix C). Following these procedures, the eligible HS sectors for asymmetry analysis were identified as follows: 14.14% (14/99) for Brazil–US exports, 10.10% (10/99) for Brazil–US imports, 10.10% (10/99) for Brazil–China exports, and 11.11% (11/99) for Brazil–China imports.

Figure 1: Brazil–US Asymmetric Exports



Source: own elaboration.

Figure 2: Brazil–US Asymmetric Imports

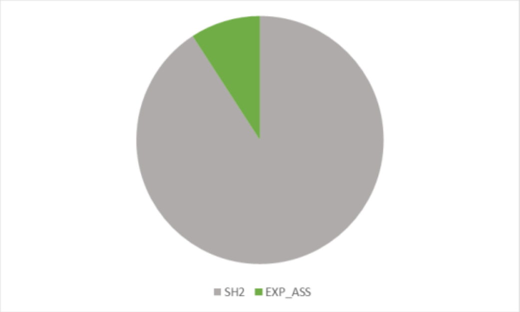


Source: own elaboration.

The Wald test, also referred to as the asymmetry test, was applied to the eligible sectors of Brazil–US and Brazil–China exports and imports. Evidence of asymmetry was identified in 12 sectors within Brazil–US exports. These sectors correspond to the following HS codes: sugars (17E), vegetables (20E), tobacco and manufactured tobacco products (24E), inorganic chemicals (28E), organic chemicals (29E), plastics and articles (39E), rubber and articles (40E), the leather sector (41E), fibrous cellulosic material (47E), iron and steel (72E), electrical machinery (85E), and arms and ammunition (93E). The Brazil–US import modality includes 9 sectors with asymmetric characteristics. These sectors are: organic chemical products (29I), essential oils for cosmetics (33I), photographic products (37I), miscellaneous chemical industry products (38I), rubber (40I) and paper for recycling (47I), aluminum (76I), miscellaneous articles of base metal (83I) and vehicles and track equipment (86I). At the HS disaggregation level, the bilateral trade flow between Brazil and the US exhibits asymmetry in 12.12% (12 out of 99) of export sectors and 9.09% (9 out of 99) of import sectors (see Figures 1 and 2).

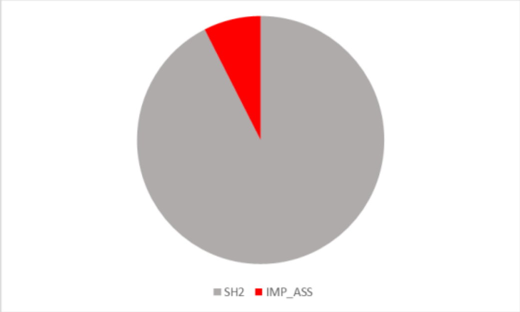
The results indicate that Brazilian export sectors to China exhibited asymmetry in 10 sectors, namely: meat (2E), oil seeds and oleaginous fruits (12E), animal or vegetable fats and oils (15E), sugars (17E), salt or sulphur (25E), ores (26E), mineral fuels (27E), organic chemicals (29E), cork and articles (45E), and paper and paperboard (48E).

Figure 3: Brazil–China Asymmetric Exports



Source: own elaboration.

Figure 4: Brazil–China Asymmetric Imports



Source: own elaboration.

The imports from China to Brazil exhibited asymmetrical characteristics in eight sectors: glass (70I), iron and steel (72I), iron or steel articles (73I), copper and articles (74I), nuclear reactors (84I), electrical machinery (85I), optical apparatus (90I), and clocks and watches (91I). Asymmetry was with 10.10% (10/99) and 8.08% (8/99) for Brazil–China exports and imports, respectively. After identifying various Brazil–US and Brazil–China HS sectors with asymmetric characteristics in the short and long run, this analysis examines the signs of the response of exports and imports in relation to the input group of positive and negative volatility in the short and long run.

Table 1 presents four HS export products from Brazil to the US, along with their respective export data and long-run asymmetry estimates. Among these products, iron and steel (72E) and arms and ammunition (93E) show a positive response to the volatility group, with statistically significant negative coefficients at the 10% level for positive volatility. This implies that a 1% increase in positive volatility leads to an average decrease of −0.28% and −0.29% in exports of iron and arms, respectively. Three export products show significant responses to the negative volatility group: tobacco (24E), with a positive sign at the 10% significance level; electrical machinery (85E), with a positive sign at the 5% level; and arms and ammunition (93E), with a negative sign at the 10% level. In other words, a 1% increase in negative volatility affects exports of tobacco, electrical machinery, and arms by +0.16%, +0.25%, and −0.32%, respectively, on average. The results suggest that positive volatility shocks had a negative long-run effect on Brazil–US bilateral exports.

Table 1: Long-run NARDL Estimates / Brazil–US Exports

Sectors	C	LnIP	LnREX	VPOS	VNEG
24E	19.794***	0.927	−1.307***	0.094	0.164*
72E	−69.835	5.991 ***	−0.215	−0.278 *	−0.231
85E	10.141*	2.744**	−0.559*	0.116	0.251**
93E	36.110***	-3.933**	−0.391	−0.288 *	−0.316*

Source: own elaboration based on Microfit 5.5 Software.
Note: ***, **, * indicate significance at 1%, 5%, and 10%, respectively.

Table 2 presents the short-run NARDL estimates for exports. The HS products in the positive volatility group were: sugars (17E), Pos(0) significant at 1%, positive sign (+). Vegetables (20E), Pos(−1) significant at 10%, positive sign (+); Pos(−4), significant at 5%, positive sign (+); and Pos(−5) significant at 5%, negative sign (−). Inorganic chemicals (28E), Pos(0) significant at 5%, positive sign (+). Organic chemicals (29E), Pos(0) significant at 5%, negative sign (−); and Pos(−1), significant at 5%, negative sign (−). Plastics (39E), Pos(0) significant at 10%, negative sign (−). Rubber (40E), Pos(0) significant at 5%, positive sign (+); Pos(−3) significant at 5%, negative sign (−); and Pos(−6) significant at 1%, negative sign (−). Leather (41E), Pos(0) significant at 5%, positive sign (+). Iron and steel (72E), Pos(−3) significant at 5%, positive sign (+); and Pos(−4) significant at 1%, negative sign (−). The most expressive results, with broader coverage in positive lags, can be understood as follows: a 1% increase in short-run positive volatility impacts rubber exports, associated with significant lags at Pos(0), +0.11%; Pos(−3), −0.10%; and Pos(−6), +0.15%.

Table 2: Short-run NARDL Estimates / Brazil–US Exports

Sectors	ΔPos(0)	ΔPos(−1)	ΔPos(−2)	ΔPos(−3)	ΔPos(−4)	ΔPos(−5)	ΔPos(−6)	ΔPos(−7)
17E	0.911 ***							
20E	−0.111	0.557*	−0.272	−0.481	0.734**	−0.592**		
28E	0.221**							
29E	−0.185**	−0.206**						
39E	0.08	−0.120*						
40E	0.112**	−0.072	−0.053	−0.102**	0.0252	−0.006	−0.147***	
41E	0.125**	−0.11						
72E	0.185	−0.151	−0.123	0.358**	−0.395***			
Sectors	**ΔNeg(0)**	**ΔNeg(−1)**	**ΔNeg(−2)**	**ΔNeg(−3)**	**ΔNeg(−4)**	**ΔNeg(−5)**	**ΔNeg(−6)**	**ΔNeg(−7)**
17E	−2.190***	0.588	−0.187	0.163	−0.575	−10.083	−0.217	1.355***
24E	0.223*							
47E	0.562*	0.465	0.896***	−0.709**	0.558*			
85E	0.094**							
93E	−0.204	0.080	0.230	−0.770***				

Source: own elaboration based on Microfit 5.5 Software.
Note: ***, **, * indicate significance at 1%, 5%, and 10%, respectively.

The selected HS products with negative volatility were: sugars (17E), Neg(0) significant at 1%, sign (−) and Neg(−7) significant at 1%, sign (−). Tobacco (24E), Neg(0) significant at 10%, sign (+). Fibrous cellulosic material (47E), Neg(0) significant at 10%, sign (+); Neg(−2) significant at 1%, sign (+); Neg(0) significant at 5%, sign (−) and Neg(−4) significant at 10%, sign (+). Electrical machinery (85E), Neg(0) significant at 5%, sign (+). Arms and ammunition (93E), Neg(−3) significant at 1%, sign (−). The most notable results, with greater coverage of negative lags, can be interpreted as follows: a 1% increase in short-run negative volatility impacts sugar exports, associated with significant lags of Neg(0), −2.19%, and Neg(−7), 1.35%.

Table 3 presents seven HS products for Brazil–US bilateral imports in the long run, with five imported products showing positive volatility: organic chemicals (29I), significant at 5% with a positive sign; essential oils (33I), significant at 10% with a positive sign; other chemical industry products (38I), significant at 10% with a positive sign; base metals (83I), significant at 5% with a positive sign; and railway vehicles (86I), significant at 5% with a positive sign. In summary, a 1% increase in positive volatility leads to a corresponding increase in bilateral imports of 0.42%, 0.59%, 0.78%, 0.64%, and 0.93%, respectively.

Regarding the negative volatility group, seven HS products were found: organic chemicals (29I), significant at 5% with a sign (+). Essential oils (33I), significant at 10% with a sign (+); cinematography goods (37I), significant at 5% with a sign (+); chemical industry products (38I), significant at 5% with a sign (+); cellulose material (47I); significant at 5% with a sign (+); base metals (83I); significant at 5% with a sign (+); railway vehicles (86I), significant at 5% with a sign (+). In other words, on average a 1% increase in negative volatility impacts imports of the above-mentioned HS products by 0.48%, 0.65%, 0.16%, 0.83%, 0.26%, 0.66% and 0.99% respectively.

Table 3: Long-run NARDL Estimates / Brazil–US Imports

Sectors	C	LnIP	Ln REX	VPOS	VNEG
29I	32.057**	−0.727	−1.906*	0.421**	0.483**
33I	88.971**	−91.434	−6.467**	0.592*	0.648*
37I	24.741	3.295***	0.046	0.046	0.159**
38I	63.415**	−47.96	−47.547	0.778**	0.831**
47I	26.277***	0.069	−19.731	0.174	0.257**
83I	17.995	44.415	−10.66	0.640**	0.661**
86I	63.778**	−41.648	−5.854***	0.928**	0.993**

Source: own elaboration based on Microfit 5.5 Software.
Note: ***, **, * indicate significance at 1%, 5%, and 10%, respectively.

Table 4 presents the short-run NARDL estimates for Brazil–US imports. Within the positive volatility group, the identified HS products were: essential oils (33I), with Pos(−5) significant at 1%, sign (+), and Pos(−6) significant at 5%, sign (−). Cinematographic products (37I), with Pos(−2) significant at 10%, sign (+), Pos(−5) significant at 1%, sign (+), and Pos(−7) significant at 10%, sign (−). Chemical industry products (38I), Pos(−6) significant at 1%, sign (−). Rubber (40I), Pos(−2) significant at 10%, sign (−), and Pos(−5) significant at 1%, sign (−). Aluminum (76I), Pos(−5) significant at 1%, sign (−). Base metals (83I), with Pos(−1) significant at 5%, sign (−), Pos(−5) significant at 1%, sign (+), and Pos(−6) significant at 5%, sign (−). Railway vehicles (86I), Pos(0) significant at 5%, sign (+), and Pos(−1) significant at 10%, sign (−). Applying elasticity analysis to the regressor with the most significant lag, corresponding to product 37I, it can be stated that a 1% increase in the positive volatility shock group impacts imports with changes of 0.69% at Pos(−2), 0.85% at Pos(−5), and −0.51% at Pos(−7).

The HS products in the negative volatility group were: organic chemicals (29I), Neg(0) significant at 10%, sign (+). Essential oils (33I), Neg(0) significant at 10%, sign (−). Cinematographic products (37I), Neg(−2) significant at 5%, sign (−). Chemical industry products (38I), Neg(0) significant at 5%, sign (−). Railway vehicles (86I), Neg(0) significant at 5%, sign (−), and Neg(−1) significant at 1%, sign (+). The largest lag for the negative volatility group was observed in sector 37I. In other words, a 1% increase in the negative volatility shock group affects cinematographic product imports with a significant lag of −1.85% at Neg(−2).

Table 4: Short-run NARDL Estimates / Brazil–US Imports

Sectors	ΔPos(0)	ΔPos(−1)	ΔPos(−2)	ΔPos(−3)	ΔPos(−4)	ΔPos(−5)	ΔPos(−6)	ΔPos(−7)
33I	0.117	−0.069	0.017	−0.044	0.0756	0.424***	−0.243**	0.117
37I	0.044	−0.315	0.693*	−0.361	−0.058	0.852***	−0.308	−0.505*
38I	0.145	−0.236	0.082	−0.211	−0.131	0.275	−0.528***	
40I	0.04	0.202	−1.466*	0.123	0.55	−2.536***		
76I	13.668	0.434	−10.537	−0.581	0.949	−2.785***		
83I	−0.099	−1.729**	0.12	−0.11	−0.948	1.995***	−1.594**	
86I	1.0527**	−0.825*						
Sectors	**ΔNeg(0)**	**ΔNeg(−1)**	**ΔNeg(−2)**	**ΔNeg(−3)**	**ΔNeg(−4)**	**ΔNeg(−5)**	**ΔNeg(−6)**	**ΔPos(−7)**
29I	0.184*							
33I	−0.614*							
37I	−0.275	−0.272	−1.854**					
38I	−0.772**							
86I	−2.739**	3.296***						

Source: own elaboration based on Microfit 5.5 Software.
Note: ***, **, * indicate significance at 1%, 5%, and 10%, respectively.

Table 5 presents two products classified by the HS for Brazil–China exports in the long run. Only meats (2E) are significant at 5% in the positive volatility group, with a negative sign. This indicates that a 1% increase in long-run positive volatility results in a −0.85% impact on meat exports. Regarding the negative volatility group, two HS products were identified: meats (2E), which showed a significant negative impact at 1%, and animal or vegetable fats and oils (15E), with a significant positive impact at 5%. In other words, a 1% increase in positive and negative volatility affects exports of these HS products by −1.07% and 0.68%, respectively.

Table 5: Long-run NARDL Estimates / Brazil–China Exports

Sectors	C	LnIP	Ln REX	VPOS	VNEG
2E	−12.632	0.122	3.828***	−0.846**	−1.072***
15E	874.306	2.804*	−2.012	0.889	0.676**

Source: own elaboration based on Microfit 5.5 Software.
Note: ***, **, * indicate significance at 1%, 5%, and 10%, respectively.

Table 6 presents the short-run NARDL estimation for Brazil–China exports. The positive volatility HS products were: meats (2E), Pos(0) significant at 5%, sign (−). Pos(−1) significant at 10%, sign (+). Pos(−2) significant at 5%, sign (+). Animal or vegetable fats and oils (15E), Pos(−3) significant at 1%, sign (−). Sugars (17E), Pos(−1) significant at 1%, sign (+). Salt or sulphur (25E), Pos(0) significant at 1%, sign (−). Ores (26E), Pos(0) significant at 1%, sign (−). Pos(−2) significant at 5%, sign (+). Mineral fuels (27E), Pos(0) significant at 10%, sign (−). Organic chemicals (29E), Pos(0) significant at 1%, sign (+). Pos(−1) significant at 10%, sign (−). Pos(−2) significant at 10%, sign (−). Pos(−4) significant at 5%, sign (+). Leather (41E), Pos(−1) significant at 1%, sign (−). The HS sector with the greatest number of lags was organic chemicals (29E), meaning that a 1% increase in the positive volatility shock group impacts organic chemicals exports with significant lags of 1.56% at Pos(0); −0.13% at Pos(−1); −0.96% at Pos(−2); and 1.18% at Pos(−4).

The HS products selected for the negative volatility group were: meats (2E), Neg(0), significant at 1%, sign (−). Oil seeds and oleaginous fruits (12E), Neg(−1), significant at 5%, sign (−); Neg(−3), significant at 5%, sign (−). Sugars (17E), Neg(0), significant at 10%, sign (−). Mineral fuels (27E), Neg(0), significant at 10%, sign (+); Neg(−1), significant at 5%, sign (+). Leather (41E), Neg(−5), significant at 10%, sign (+); Neg(−7), significant at 10%, sign (−). Cork (45E), Neg(0), significant at 10%, sign (+). Paper (48E), Neg(−3), significant at 1%, sign (+); Neg(−7), significant at 5%, sign (−). Two HS sectors showed the largest lags: leather (41E) and paper (48E). In other words, a 1% increase in the negative volatility shock group impacts raw hides exports with significant lags of 4.14% at Neg(−5); 3.86% at Neg(−6); −3.73% at Neg(−7). Regarding the second product, a 1% increase in the negative volatility group had a significant impact on paper exports of 7.51% at Neg(−3); −6.49% at Neg(−7).

Table 6: Short-run NARDL Estimates / Brazil–China Exports

Sectors	ΔPos(0)	ΔPos(−1)	ΔPos(−2)	ΔPos(−3)	ΔPos(−4)	ΔPos(−5)	ΔPos(−6)	ΔPos(−7)
2E	−2.155**	1.835*	2.090**					
15E	1.700	−11.788	−0.983	−3.540***				
17E	−1.159	6.599***						
25E	−2.179***							
26E	1.998***	0.680	1.602**					
27E	−2.330*							
29E	1.561***	−0.127*	−0.959*	0.365	1.178**			
41E	−0.240	−3.730***						

Sectors	ΔNeg(0)	ΔNeg(−1)	ΔNeg(−2)	ΔNeg(−3)	ΔNeg(−4)	ΔNeg(−5)	ΔNeg(−6)	ΔNeg(−7)
2E	−1.716***							

12E	−0.294	−4.811**	−3.024	−3.779**				
17E	−1.548*							
27E	0.085*	4.903**						
41E	−0.228	−2.284	2.243	3.191	2.210	4.145*	3.863*	−3.730*
45E	5.060*	5.061						
48E	−4.156	−4.156	0.626	7.513***	3.052	1.787	3.264	−6.490**

Source: own elaboration based on Microfit 5.5 Software.
Note: ***, **, * indicate significance at 1%, 5%, and 10%, respectively.

Table 7 displays two HS products for long-run Brazil–China imports. Asymmetry was only found in the positive volatility group, with glass (70I) and copper (74I) showing significance at 5% and 10%, respectively. This means that a 1% increase in positive volatility affects the imports of these bilateral HS products from Brazil to China by 0.18% and 0.33%, respectively.

Table 7: Long-run NARDL Estimates / Brazil–China Imports

Sectors	C	LnIP	Ln REX	VPOS	VNEG
70I	−16.990***	7.629***	−0.609	0.179**	0.094
74I	131.645	4.4143***	−3.811***	0.328*	0.289

Source: own elaboration based on Microfit 5.5 Software.
Note: ***, **, * indicate significance at 1%, 5%, and 10%, respectively.

Table 8 presents the short-run NARDL estimates for Brazil–China imports. The positive volatility group HS products were: glass (70I), Pos(0), significant at 5%, positive sign (+). Iron or steel articles (73I), Pos(0), significant at 5%, positive sign (+); Pos(–2), significant at 10%, negative sign (–). Copper (74I), Pos(–4), significant at 5%, negative sign (–); Pos(–6), significant at 5%, negative sign (–); Pos(–7), significant at 1%, positive sign (+). Nuclear reactors (84I), Pos(–3), significant at 5%, positive sign (+); Pos(–5), significant at 1%, positive sign (+). Electrical machinery (85I), Pos(–4), significant at 5%, negative sign (–); Pos(–5), significant at 5%, positive sign (+). Optical apparatus (90I), Pos(0), significant at 5%, negative sign (–); Pos(–1), significant at 5%, positive sign (+). The HS sector with the longest lag was copper (74I), meaning a 1% increase in the positive volatility group affects copper imports with significant lags of –1.11% at Pos(–4), –1.05% at Pos(–6), and 1.14% at Pos(–7).

The negative volatility group HS product was limited to iron or steel (72I), Neg(–1), significant at 10%, negative sign (–); Neg(–3), significant at 5%, positive sign (+). Thus, a 1% increase in the negative volatility group affects iron or steel imports with significant lags of –0.75% at Neg(–1) and 0.97% at Neg(–3).

Table 8: Short-run NARDL Estimates / Brazil–China Imports

Sectors	ΔPos(0)	ΔPos(−1)	ΔPos(−2)	ΔPos(−3)	ΔPos(−4)	ΔPos(−5)	ΔPos(−6)	ΔPos(−7)
70I	0.191**							
73I	0.913**	0.61	−0.913*					
74I	0.723	0.716	0.289	0.175	−1.110**	0.414	−1.045**	1.144***
84I	−0.301	-0.651	−13.555	1.832**	−11.494	1.761***		
85I	0.07	0.864	−0.113	0.222	−2.514**	1.392**		
90I	−40.381	4.570*						
91I	−1.791**	2.060**						
Sectors	**ΔNeg(0)**	**ΔNeg(−1)**	**ΔNeg(−2)**	**ΔNeg(−3)**	**ΔNeg(−4)**	**ΔNeg(−5)**	**ΔNeg(−6)**	**ΔNeg(−7)**
72I	0.259	-0.748*	-0.347	0.968**				

Source: own elaboration based on Microfit 5.5 Software.
Note: ***, **, * indicate significance at 1%, 5%, and 10%, respectively.

The estimated regression coefficients allow for a nuanced interpretation. In the context of export flows, a positive shock in the bilateral real exchange rate volatility typically signals a depreciation of the domestic currency relative to the foreign currency. This, in turn, tends to enhance Brazil's export competitiveness by making domestic goods more affordable to foreign buyers. Conversely, a negative shock in volatility suggests a potential appreciation of the domestic currency, which would likely dampen export performance by increasing the relative price of Brazilian goods abroad.

From the perspective of import flows, a positive volatility shock may be associated with a real appreciation of the domestic currency, thereby reducing the cost of imported goods and encouraging higher import volumes. On the other hand, a negative volatility shock implies a real depreciation, which raises the cost of foreign goods and tends to curb import demand.

These distinctions between positive and negative exchange rate volatility shocks underscore the relevance of this study, especially when positioned against prior empirical literature. While existing studies often contrast symmetric and asymmetric specifications—typically favoring the latter—they rarely offer an in-depth interpretation of the nonlinear and asymmetric coefficients. This paper addresses that gap by clarifying how exchange rate uncertainty is perceived and responded to by economic agents over time, depending on whether the domestic currency is strengthening or weakening, and how such dynamics affect trade flows.

5. Conclusion

This study achieved its objective by conducting an in-depth analysis of disaggregated products at the HS two-digit level between Brazil and its two main trading partners, with a particular focus on bilateral exports and imports. The analysis commenced with an investigation of the signs and magnitudes of the NARDL regression parameters, which indicated the presence of asymmetric characteristics in the input variable—specifically, the positive and negative volatility groups of the bilateral real exchange rate between Brazil and the US and between Brazil and China, in relation to the bilateral trade responses in exports and imports. Following the preliminary unit root tests, cointegration and stability diagnostics of the NARDL model, the study identified asymmetry between the short- and long-run periods for the Brazil–US export flow (12.12%) and import flow (9.09%) (see Figures 1 and 2). Regarding HS products, asymmetry was identified in Brazil–China trade, with 10.10% for exports and 8.08% for imports (see Figures 3 and 4). As a result, the NARDL model was deemed unrepresentative, failing to achieve an asymmetric significance of at least 1/3 in the historical series between exports and imports in the short and long run for both Brazil–US and Brazil–China. Furthermore, the stability diagnostic analysis (primarily the serial correlation test) revealed a notable decline in asymmetric representativeness for the NARDL model.

This study advances the empirical literature by conducting a comprehensive investigation into the asymmetric effects of exchange rate volatility on international trade flows. Trade flows are disaggregated into 99 industries between Brazil and the US and between Brazil and China, taking into account exports and imports, positive and negative volatility groups, and both short- and long-run dynamics. A comparison of this study with existing empirical literature reveals that the majority of empirical studies have identified superior representativeness for asymmetric models incorporating variations between the short- and long-run effects across specific industrial sectors in each country under investigation.

However, the study revealed that the Brazil–US (exports 12.12% and imports 9.09%) and Brazil–China (exports 10.10% and imports 8.08%) trade relationships were not sufficiently representative. Nevertheless, a relative balance was observed between the short- and long-run analysis. Moreover, the sectors that exhibited the most notable performance were: iron and arms (Brazil–US exports, long run, positive volatility); tobacco, electrical machinery and arms (Brazil–US exports, long run, negative volatility); sugars, vegetables, inorganic chemicals, organic chemicals, rubber, hides and iron (Brazil–US exports, short run, positive volatility); sugars, tobacco, paper, electrical machinery and arms (Brazil–US exports, short run, negative volatility); organic chemicals, chemical industry, base metals and railway vehicles (Brazil–US imports, long run, positive volatility); organic chemicals, oils, cinematography, chemical industry, cellulose, metals, railway vehicles (Brazil–US imports, long run, negative volatility); oils, cinematography, chemical industry, rubber, aluminum, base metals and railway vehicles (Brazil–US imports, short run, positive volatility); oils, cinematography goods, chemical industry, railway vehicles (Brazil–US imports, short run, negative volatility); meat (Brazil–China exports, long run, positive volatility), meat and fats (Brazil–US exports, long run, negative volatility); meats, fats, sugars, salt or sulphur, ores, organic chemicals, hides, (Brazil–US exports, short-run, positive volatility); meats, seeds, sugars, mineral fuels, hides, cork, paper, (Brazil–US exports, short-run, negative volatility); glass, copper (Brazil–China imports, long run, positive volatility); glass, iron, copper, nuclear reactors, electrical machinery and optical apparatus (Brazil–China imports, short run, positive volatility); iron (Brazil–China imports, short run, negative volatility). Ultimately, the investigation of long-run negative volatility in a range of industries revealed no evidence of asymmetry in the case of Brazil–China imports.

The nonlinear and asymmetric results presented in this study are relevant for public policymakers, as the research captured the distinct influences of both positive and negative exchange rate volatility on trade flows between Brazil and its two main trading partners. The findings also partially justify the divergent behavior of economic agents when the exchange rate appreciates or depreciates across different industrial sectors. In light of this, the study reinforces the empirical evidence reviewed, highlighting the role of asymmetric models in understanding the impact of exchange rate volatility on international trade flows through a disaggregated analysis of 99 industries. Moreover, consistent with the findings of Bahmani-Oskooee and Aftab (2017), this study suggests that future research should employ asymmetric approaches to assess the potential impact of exchange rate volatility on global trade flows, since symmetric models may yield incomplete or imprecise results.

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Appendix A- Variable Descriptions and References

Variable	Description	Reference
X	Monthly bilateral exports (FOB) from Brazil−US and Brazil−China in US dollars, for the 99 HS products.	<http://comexstat.mdic.gov.br/pt/geral>.
M	Monthly bilateral imports (FOB) from Brazil−US and Brazil−China in US dollars, for the 99 HS products.	<http://comexstat.mdic.gov.br/pt/geral>.
IP	Brazil's monthly Industrial Production Index, used as a proxy for the country's GDP.	<https://www.oecd.org/fr/>.
IP*	Monthly Industrial Production Index of China and the US.	<https://www.oecd.org/fr/>.
REX	The bilateral real exchange rate is calculated by dividing the nominal exchange rate (in BRL per unit of foreign currency) by the ratio between Brazil's Producer Price Index (IPA-EP-DI/FGV) and the foreign country's Producer Price Index (PPI).	<http://www.ipeadata.gov.br/Default.aspx>.
V	Volatility is calculated based on the REX variable using a GARCH (p, q) structure. For more details on the construction of the volatility variable (Vt), see Appendix B.	

Appendix B- Construction of the Volatility Variable (Vt)

The generalized specification of the GARCH (p, q) model can be understood in three steps:
1. Estimate the most appropriate AR(q) model:

$$y_t = a_0 + a_1 y_{t-1} + \cdots + a_q y_{q-1} + \epsilon_t = a_0 + \sum_{i=1}^{q} a_i y_{t-i} + \epsilon_t \tag{1}$$

2. Compute and map the autocorrelations of ϵ^2:

$$\rho = \frac{\sum_{t=i+1}^{T} (\hat{\epsilon}_t^2 - \hat{\sigma}_t^2)(\hat{\epsilon}_{t-1}^2 - \hat{\sigma}_{t-1}^2)}{\sum_{t=1}^{T} (\hat{\epsilon}_t^2 - \hat{\sigma}_t^2)^{\,2}} \tag{2}$$

3. Finally, the asymptotic standard deviation—i.e., for large samples—of $\rho(i)$ and $1/\sqrt{T}$. Individual values greater than these indicate GARCH errors. To estimate the total number of lags, the Ljung-Box test is used until the value of these is less than 10% significant. The Ljung-Box Q-statistic follows a x^2 distribution with n degrees of freedom, if the squares of the residuals ϵ_t^2 are uncorrelated. It is recommended to consider up to T/4 values of n. The null hypothesis states that there are no ARCH or GARCH errors. Rejecting the null hypothesis implies the existence of such errors in the conditional variance.

According to Bahmani-Oskooee and Aftab (2017), exchange rate volatility will be measured using the GARCH (1,1) metric. Both the autoregressive (AR) and moving average (MA) components of the model are of the first order. The main input for the volatility variable, REX_t, follows a random walk structure: $REX_t = \alpha_0 + \alpha_1 REX_{t-1} + \varepsilon_t$, with mean zero errors $E(\varepsilon)$=0, and constant variance $V(\varepsilon) = h^2$. The reduced and main forms of the GARCH(1,1) estimation are represented below:

$$REX_t = \alpha_0 + \alpha_1 REX_{t-1} + \varepsilon_t \tag{3}$$

$$h_t^2 = \beta_0 + \beta_1 \varepsilon_{t-1}^2 + \beta_2 \varepsilon_{t-2}^2 + \cdots + \beta_q \varepsilon_{t-q}^2 + \emptyset_1 h_{t-1}^2 + \emptyset_2 h_{t-2}^2 + \cdots + \emptyset_p h_{t-p}^2 \tag{4}$$

First, a random walk process was estimated based on the real exchange rate variable REX_t, as in Equation 3. Then, the conditional variance was estimated using $\varepsilon_t = h_t^2$, from Equation 4. This study applied ARCH and GARCH (p, q) models to measure exchange rate volatility. As stated by Bahmani-Oskooee and Hegerty (2007), empirical studies in the 21st century dealing with bilateral and sectoral trade structures have commonly employed this approach. In other words, time series research combined with models that use conditional variance such as GARCH (p, q) has proven particularly useful in modeling bilateral real exchange rate volatility.

Appendix C- NARDL Stability and Cointegration Diagnostics

Table C1: Brazil–US Exports

Sectors	NARDL	F-bound	LMpv	ARCHpv	CUSUM	CUSUMSQ
3E	(7,1,7,0,0)	26.118**	0.027	0.109	YES	NO
8E	(2,2,0,2,2)	6.894**	0.626	0.473	NO	NO
9E	(4,0,3,0,0)	8.232**	0.9	0.000	YES	YES
16E	(7,1,0,0,0)	6.091 **	0.054	0.210	SIM	NO
17E	(6,7,1,8,1)	9.823 **	0.426	0.275	YES	YES
20E	(3,1,0,0,5)	10.365 **	0.768	0.005	NO	YES
22E	(4,1,0,0,0)	4.802**	0.333	0.162	YES	YES
24E	(8,2,0,0,0)	13.009**	0.67	0.936	YES	YES
26E	(0,3,1,0,0)		0.706	0.257	YES	NO
27E	(1,2,3,0,0)	23.595**	0.498	0.227	YES	NO
28E	(3,7,0,0,1)	6.148**	0.605	0.161	YES	YES
29E	(3,0,1,0,2)	9.793**	0.532	0.284	YES	YES
39E	(2,1,4,0,2)	5.657**	0.226	0.362	YES	YES
40E	(3,0,2,0,7)	2.610 *	0.973	0.535	YES	YES
41E	(2,3,5,0,2)	9.285**	0.688	0.265	NO	YES
44E	(8,8,0,2,0)	2.609	0.28	0.001	YES	YES
47E	(2,0,0,5,0)	21.078**	0.431	0.741	YES	NO
48E	(8,0,0,0,6)	2.573	0.007	0.020	NO	YES
63E	(3,1,0,7,7)	2.373	0.482	0.000	NO	NO
64E	(6,4,1,6,0)	1.32	0.948	0.678	YES	YES
68E	(8,0,2,0,4)	1.713	0.025	0.272	YES	NO
69E	(8,8,0,0,0)	3.506	0.022	0.403	YES	NO
71E	(8,4,0,0,0)	1.506	0.531	0.051	YES	NO
72E	(2,5,0,0,4)	8.479**	0.583	0.128	YES	NO
73E	(3,1,3,0,0)	4.297**	0.207	0.001	YES	YES
76E	(6,4,0,0,0)	1.021	0.411	0.470	YES	YES
84E	(3,7,5,1,0)	4.725**	0.456	0.051	YES	YES
85E	(2,2,0,0,2)	7.041**	0.365	0.472	YES	YES
87E	(8,6,6,0,0)	3.514	0.79	0.814	YES	NO
88E	(6,1,2,0,0)	4.267*	0.613	0.002	YES	NO
90E	(7,6,3,0,1)	2.631	0.485	0.856	YES	NO

93E	(3,1,0,4,1)	4.906**	0.918	0.743	YES	YES
94E	(8,6,2,4,1)	3.493	0.213	0.485	YES	NO

Source: own elaboration based on Microfit 5.5 software.
Note: ***, **, * indicate significance at 1%, 5%, and 10%, respectively.
Note: *pv* refers to the p-value of the test.

Table C2: Brazil–US Imports

Sectors	NARDL	F-bound	LM^{pv}	$ARCH^{pv}$	CUSUM	CUSUMSQ
10I	(4,0,0,0,5)	3.232	0.611	0.601	NO	YES
21I	(8,0,0,0,0)	2.166	0.002	0.785	YES	NO
22I	(6,0,0,0,0)	2.555	0.674	0.102	YES	YES
26I	(8,0,0,4,7)	2.899	0.120	0.504	YES	NO
27I	(8,0,0,0,0)	1.843	0.134	0.012	YES	NO
28I	(8,0,4,1,7)	2.271	0.001	0.532	YES	NO
29I	(6,0,4,0,1)	3.541*	0.403	0.964	YES	NO
30I	(5,0,0,8,3)	2.071	0.654	0.083	YES	YES
31I	(7,0,1,0,0)	2.469	0.807	0.475	YES	YES
32I	(8,0,3,0,6)	3.107	0.035	0.221	YES	YES
33I	(8,5,4,1,7)	4.259**	0.344	0.086	NO	NO
34I	(6,0,2,0,0)	2.342	0.256	0.070	YES	NO
37I	(6,0,0,3,8)	10.858**	0.737	0.297	YES	NO
38I	(7,1,4,1,7)	3.477*	0.168	0.475	YES	YES
39I	(8,0,0,0,0)	2.195	0.161	0.023	YES	YES
40I	(3,0,0,0,6)	23.985**	0.934	0.141	YES	NO
47I	(7,0,4,7,0)	4.280**	0.970	0.248	YES	YES
48I	(0,0,0,0,0)		0.000	0.523	YES	YES
72I	(5,0,4,1,7)	4.109**	0.021	0.453	YES	YES
73I	(7,0,0,0,0)	4.954**	0.903	0.990	YES	YES
76I	(6,0,0,0,6)	11.957**	0.168	0.669	YES	YES
83I	(7,0,4,1,7)	6.597**	0.714	0.433	YES	YES
84I	(7,0,0,0,0)	2.840	0.933	0.445	YES	NO
85I	(0,0,0,0,0)		0.345	0.443	YES	NO
86I	(8,0,4,1,2)	4.562**	0.257	0.003	YES	NO
87I	(5,2,2,0,7)	3.459*	0.037	0.026	YES	NO
88I	(7,0,0,0,0)	3.546	0.916	0.769	YES	YES
89I	(7,0,4,1,8)	5.428**	0.468	0.334	NO	YES

90I	(7,0,0,0,7)	7.925**	0.628	0.711	YES	YES

Source: own elaboration based on Microfit 5.5 software.
Note: ***, **, * indicate significance at 1%, 5%, and 10%, respectively.
Note: *pv* refers to the p-value of the test.

Appendix D- Unit Root Test for the Variables in the NARDL Model

Figure D1: Brazil–US Exports (ADF)

	$I(0)^{PV}$	$I(1)^{PV}$	$I(2)^{PV}$		$I(0)^{PV}$	$I(1)^{PV}$	$I(2)^{PV}$
LN16E	0.0001			LN71E			0
LN17E	0.0000			LN72E	0.0009		
LN20E	0.0000			LN73E	0.0147		
LN22E	0.0191			LN76E	0.0000		
LN24E		0.0000		LN84E		0.0000	
LN26E	0.0001			LN85E		0.0000	
LN27E	0.0000			LN87E		0.0000	
LN28E	0.0164			LN88E		0.0000	
LN29E	0.0047			LN8E		0.0000	
LN39E	0.0038			LN90E	0.0683		
LN3E		0.0000		LN93E	0.0290		
LN40E		0.0000		LN94E	0.0543		
LN41E	0.0031			LN9E	0.0085		
LN44E		0.0091		LNIP			
LN47E	0.0000			LNTCR		0.0000	
LN48E		0.0000		VOLNEG		0.0000	
LN63E		0.0000		VOLPOS		0.0000	
LN64E		0.0188					
LN68E	0.0618						
LN69E		0.0000					

Source: own elaboration.
Note: *pv* refers to the p-value of the test.

Figure D2: Brazil–US Exports (Phillips-Perron)

	I(0)^{PV}	I(1)^{PV}	I(2)^{PV}		I(0)^{PV}	I(1)^{PV}	I(2)^{PV}
LN16E	0.0000			LN71E	0.0000		
LN17E	0.0000			LN72E	0.0000		
LN20E	0.0000			LN73E	0.0000		
LN22E	0.0001			LN76E	0.0010		
LN24E	0.0000			LN84E	0.0000		
LN26E	0.0000			LN85E		0.0000	
LN27E	0.0000			LN87E		0.0000	
LN28E	0.0000			LN88E	0.0000		
LN29E	0.0000			LN8E	0.0128		
LN39E	0.0000			LN90E	0.0033		
LN3E	0.0001			LN93E	0.0001		
LN40E	0.0148			LN94E		0.0000	
LN41E	0.0000			LN9E	0.0174		
LN44E		0.0000		LNIP			
LN47E	0.0000			LNTCR		0.0000	
LN48E	0.0000			VOLNEG		0.0000	
LN63E		0.0000		VOLPOS		0.0000	
LN64E		0.0000					
LN68E	0.0042						
LN69E		0.0000					

Source: own elaboration.
Note: *pv* refers to the p-value of the test.

Figure D3: Brazil–US Exports (Breakpoint Dickey-Fuller)

	I(0)^{PV}	I(1)^{PV}	I(2)^{PV}		I(0)^{PV}	I(1)^{PV}	I(2)^{PV}
LN16E	0.0100			LN71E	0.0100		
LN17E	0.0100			LN72E	0.0100		
LN20E	0.0100			LN73E	0.0100		
LN22E	0.0100			LN76E	0.0100		
LN24E	0.0100			LN84E	0.0100		
LN26E	0.0100			LN85E	0.0458		
LN27E	0.0100			LN87E	0.0130		
LN28E	0.0100			LN88E	0.0100		
LN29E	0.0100			LN8E	0.0100		
LN39E	0.0100			LN90E	0.0100		
LN3E	0.0100			LN93E	0.0100		
LN40E		0.0100		LN94E		0.0100	
LN41E	0.0100			LN9E	0.0100		
LN44E		0.0100		LNIP			0.0100
LN47E	0.0100			LNTCR		0.0100	
LN48E	0.0100			VOLNEG		0.0100	
LN63E	0.0100			VOLPOS		0.0100	
LN64E		0.0100					
LN68E	0.0236						
LN69E	0.0792						

Source: own elaboration.
Note: *pv* refers to the p-value of the test.

Figure D4: Brazil–US Imports (ADF)

	$I(0)^{PV}$	$I(1)^{PV}$	$I(2)^{PV}$		$I(0)^{PV}$	$I(1)^{PV}$	$I(2)^{PV}$
LN10I	0.0000			LN76I	0.0000		
LN21I	0.0809			LN83I	0.0855		
LN22I		0.0000		LN84I		0.0000	
LN26I	0.0000			LN85I	0.0000		
LN27I	0.0000			LN86I	0.0000		
LN28I	0.0005			LN87I	0.0012		
LN29I	0.0760			LN88I	0.0000		
LN30I		0.0000		LN89I		0.0000	
LN31I	0.0000			LN90I	0.0852		
LN32I	0.0660			LNIP		0.0000	
LN33I		0.0000		LNTCR		0.0000	
LN34I		0.0000		VOLNEG		0.0000	
LN37I		0.0000		VOLPOS		0.0000	
LN38I	0.0223						
LN39I		0.0000					
LN40I		0.0000					
LN47I		0.0000					
LN48I		0.0000					
LN72I	0.0001						
LN73I		0.0000					

Source: own elaboration.
Note: *pv* refers to the p-value of the test.

Table D5: Brazil–US Imports (Phillips-Perron)

	$I(0)^{PV}$	$I(1)^{PV}$	$I(2)^{PV}$		$I(0)^{PV}$	$I(1)^{PV}$	$I(2)^{PV}$
LN10I	0.0000			LN76I	0.0000		
LN21I	0.0000			LN83I	0.0000		
LN22I	0.0000			LN84I	0.0000		
LN26I	0.0000			LN85I	0.0000		
LN27I	0.0000			LN86I	0.0000		
LN28I	0.0000			LN87I	0.0000		
LN29I	0.0000			LN88I	0.0000		
LN30I	0.0000			LN89I	0.0000		
LN31I	0.0000			LN90I	0.0000		
LN32I	0.0000			LNIP		0.0000	
LN33I	0.0000			LNTCR		0.0000	
LN34I	0.0000			VOLNEG		0.0000	
LN37I	0.0000			VOLPOS		0.0000	
LN38I	0.0000						
LN39I	0.0000						
LN40I	0.0000						
LN47I	0.0000						
LN48I	0.0000						
LN72I	0.0000						
LN73I	0.0000						

Source: own elaboration.
Note: *pv* refers to the p-value of the test.

Figure D6: Brazil–US Imports (Breakpoint Dickey-Fuller)

	$I(0)^{PV}$	$I(1)^{PV}$	$I(2)^{PV}$		$I(0)^{PV}$	$I(1)^{PV}$	$I(2)^{PV}$
LN10I	0.0100			LN76I	0.0100		
LN21I	0.0100			LN83I	0.0100		
LN22I	0.0100			LN84I	0.0100		
LN26I	0.0100			LN85I	0.0100		
LN27I	0.0100			LN86I	0.0100		
LN28I	0.0100			LN87I	0.0100		
LN29I	0.0100			LN88I	0.0100		
LN30I	0.0100			LN89I	0.0100		
LN31I	0.0100			LN90I	0.0100		
LN32I	0.0100			LNIP		0.0100	
LN33I	0.0100			LNTCR		0.0100	
LN34I	0.0100			VOLNEG		0.0100	
LN37I	0.0100			VOLPOS		0.0100	
LN38I	0.0100						
LN39I	0.0100						
LN40I	0.0100						
LN47I	0.0100						
LN48I	0.0100						
LN72I	0.0100						
LN73I	0.0100						

Source: own elaboration.
Note: PV, probability value.

Figure D7: Brazil–China Exports (ADF)

	$I(0)^{PV}$	$I(1)^{PV}$	$I(2)^{PV}$		$I(0)^{PV}$	$I(1)^{PV}$	$I(2)^{PV}$
LN12E	0.0055			LNN85E	0.0271		
LN15E	0.0158			LNIP		0.0000	
LN17E	0.0002			LNTCR		0.0000	
LN24E	0.0000			VOLNEG		0.0000	
LN25E	0.0000			VOLPOS		0.0000	
LN26E		0.0000					
LN27E		0.0000					
LN29E		0.0000					
LN2E		0.0000					
LN30E		0.0000					
LN39E		0.0001					
LN40E	0.0086						
LN41E		0.0000					
LN44E	0.1076						
LN45E		0.0000					
LN47E	0.1066						
LN48E	0.0626						
LN72E		0.0000					
LN73E	0.0208						
LN74E	0.0401						

Source: own elaboration.
Note: PV, probability value.

Figure D8: Brazil–China Exports (Phillips-Perron)

	$I(0)^{PV}$	$I(1)^{PV}$	$I(2)^{PV}$		$I(0)^{PV}$	$I(1)^{PV}$	$I(2)^{PV}$
LN12E	0.0000			LNN85E	0.0000		
LN15E	0.0000			LNIP		0.0000	
LN17E	0.0000			LNTCR		0.0000	
LN24E	0.0000			VOLNEG		0.0000	
LN25E	0.0000			VOLPOS		0.0000	
LN26E	0.0000						
LN27E	0.0000						
LN29E	0.0000						
LN2E	0.0000						
LN30E	0.0000						
LN39E	0.0000						
LN40E	0.0000						
LN41E	0.0000						
LN44E	0.0000						
LN45E	0.0000						
LN47E	0.0000						
LN48E	0.0000						
LN72E	0.0000						
LN73E	0.0000						
LN74E	0.0000						

Source: own elaboration.
Note: PV, probability value.

Figure D9: Brazil–China Exports (Breakpoint Dickey-Fuller)

	$I(0)^{PV}$	$I(1)^{PV}$	$I(2)^{PV}$		$I(0)^{PV}$	$I(1)^{PV}$	$I(2)^{PV}$
LN12E	0.0100			LN85E	0.0100		
LN15E	0.0100			LNIP		0.0100	
LN17E	0.0100			LNTCR		0.0100	
LN24E	0.0100			VOLNEG		0.0100	
LN25E	0.0100			VOLPOS		0.0100	
LN26E	0.0100						
LN27E	0.0100						
LN29E	0.0100						
LN2E	0.0100						
LN30E	0.0100						
LN39E	0.0100						
LN40E	0.0100						
LN41E	0.0100						
LN44E	0.0100						
LN45E	0.0100						
LN47E	0.0100						
LN48E	0.0100						
LN72E	0.0100						
LN73E	0.0100						
LN74E	0.0100						

Source: own elaboration.
Note: PV, probability value.

Figure D10: Brazil–China Imports (ADF)

	$I(0)^{PV}$	$I(1)^{PV}$	$I(2)^{PV}$		$I(0)^{PV}$	$I(1)^{PV}$	$I(2)^{PV}$
LN27M		0.0000		LN73M		0.0000	
LN28M	0.0205			LN74M		0.0000	
LN29M		0.0000		LN76M		0.0000	
LN30M		0.0000		LN82M		0.0000	
LN31M		0.0000		LN83M		0.0000	
LN32M	0.0267			LN84M		0.0000	
LN38M		0.0000		LN85M		0.0000	
LN39M		0.0000		LN86M		0.0000	
LN3M		0.0000		LN87M		0.0000	
LN40M		0.0000		LN89M		0.0000	
LN42M		0.0000		LN90M		0.0000	
LN54M		0.0000		LN91M		0.0000	
LN55M	0.0236			LN92M		0.0000	
LN60M		0.0000		LN95M		0.0000	
LN61M	0.0166			LN96M		0.0034	
LN62M		0.0000		LN97M		0.0000	
LN63M		0.0085		LNIP		0.0000	
LN6M		0.0000		LNTCR		0.0000	
LN70M		0.0034		VOLNEG		0.0000	
LN72M		0.0000		VOLPOS		0.0000	

Source: own elaboration.
Note: PV, probability value.

Figure D11: Brazil–China Imports (Phillips-Perron)

	$I(0)^{PV}$	$I(1)^{PV}$	$I(2)^{PV}$		$I(0)^{PV}$	$I(1)^{PV}$	$I(2)^{PV}$
LN27M	0.0000			LN73M	0.0000		
LN28M	0.0000			LN74M	0.0000		
LN29M	0.0000			LN76M	0.0000		
LN30M	0.0000			LN82M	0.0000		
LN31M	0.0000			LN83M	0.0000		
LN32M	0.0000			LN84M	0.0000		
LN38M	0.0000			LN85M	0.0000		
LN39M	0.0000			LN86M	0.0000		
LN3M	0.0000			LN87M	0.0000		
LN40M	0.0000			LN89M	0.0000		
LN42M	0.0000			LN90M	0.0000		
LN54M	0.0000			LN91M	0.0000		
LN55M	0.0000			LN92M	0.0000		
LN60M	0.0000			LN95M	0.0000		
LN61M	0.0000			LN96M	0.0000		
LN62M	0.0000			LN97M	0.0000		
LN63M	0.0000			LNIP		0.0000	
LN6M	0.0000			LNTCR		0.0000	
LN70M	0.0012			VOLNEG		0.0000	
LN72M	0.0000			VOLPOS		0.0000	

Source: own elaboration.
Note: PV, probability value.

Figure D12: Brazil–China Imports (Breakpoint Dickey-Fuller)

	$I(0)^{PV}$	$I(1)^{PV}$	$I(2)^{PV}$		$I(0)^{PV}$	$I(1)^{PV}$	$I(2)^{PV}$
LN27M	0.0100			LN73M	0.0100		
LN28M	0.0100			LN74M	0.0100		
LN29M	0.0100			LN76M	0.0100		
LN30M	0.0100			LN82M	0.0100		
LN31M	0.0100			LN83M	0.0100		
LN32M	0.0100			LN84M	0.0100		
LN38M	0.0100			LN85M	0.0100		
LN39M	0.0100			LN86M	0.0100		
LN3M	0.0100			LN87M	0.0100		
LN40M	0.0100			LN89M	0.0100		
LN42M	0.0100			LN90M	0.0100		
LN54M	0.0100			LN91M	0.0100		
LN55M	0.0100			LN92M	0.0100		
LN60M	0.0100			LN95M	0.0100		
LN61M	0.0100			LN96M	0.0100		
LN62M	0.0100			LN97M	0.0100		
LN63M	0.0100			LNIP		0.0100	
LN6M	0.0100			LNTCR		0.0100	
LN70M	0.0100			VOLNEG		0.0100	
LN72M	0.0100			VOLPOS		0.0100	

Source: own elaboration.
Note: PV, probability value.