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Dynamic of Brazilian Foreign Trade by Technological Intensity

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Abstract

This paper aims to investigate the long-run relationship between the real exchange rate and the Brazilian trade balance disaggregated by technological intensity classification, i.e., High Tech, Medium-High Tech, Medium Low Tech, and Low Tech, using monthly data from the period of January 2000 to December 2022. To achieve this aim, time-varying cointegration methodology is used, as it is understood that a linear approach is not well suited for developing economies, that face much influence from external events and internal turmoils, which is just the case of Brazil. It was found that, from the 4 sectors, only the low-tech sector has the usually expected signals, that is, a benefit from exchange depreciation, but even for this industry, this positive effect has been diminishing since 2009, due to structural changes in the Brazilian agricultural sector, which accounts for much of the added value in the low-tech goods. The dynamic real exchange rate elasticities for the medium-high and medium-low tech industries oscilated much throughout the time frame of the study, revealing the great influence of external and internal shocks in the change of the trajectory of these elasticities. The high-tech sector presented opposite signals in the estimated elasticities, revealing that exchange rate appreciations benefit it, probably due to its dependency on imported inputs.

Keywords: real exchange rate, marshall-lerner condition, technological intensity classification, time-varying cointegration

1. Introduction

The trade balance stands out as a pivotal variable in the analysis of a nation's foreign trade. Conventionally, three primary factors influence the trade balance: domestic and foreign demands—typically represented by income levels—as increased demands often lead to higher import levels; and the real exchange rate, which directly impacts the relative prices between different economies.

The relationship between real exchange rates and trade balances is not a straightforward or singular one. The Marshall-Lerner condition (MLC) is the most traditional approach, suggesting that a real currency depreciation will, in the long run, lead to an improvement in the trade balance, in basic terms. However, several conditions must be met for this proposition to hold true, as it relies on the elasticities of demand for imports domestically and abroad.

The Marshall-Lerner condition (MLC) pertains to the long run. In contrast, in the short run, the relationship can be inverse. This phenomenon is known as the J-Curve, initially theorized by Magee (1973) and subsequently empirically tested by Bahmani-Oskooee (1985). The J-Curve suggests that following a currency depreciation, there may be an initial deterioration in the trade balance before potential long-term improvements occur.

Like the MLC, the relationship described by the J-Curve is not straightforward. Both conditions are contingent upon various factors such as the country in question, the prevailing macroeconomic conditions, and even specific economic sectors. This complexity contributes to the vast literature on this topic and the considerable variability in results observed across different countries, sectors, time frames, and methodological approaches.

In the case of Brazil, empirical studies often fail to converge on consistent results due to variations in methodologies, sectors examined, and time frames considered. Bahmani-Oskooee, Harvey, and Hegerty (2014) synthesized empirical research on Brazil, revealing a lack of consensus regarding the applicability of the J-Curve

and MLC to the country. Presently, research on Brazil's trade balance has progressed, focusing on new methodologies and sector-specific analyses to better understand the intricacies of its trade dynamics.

Serdar and Hakan (2017) characterize Brazil as a particularly unique laboratory for examining the relationship between the real exchange rate and the trade balance. This is primarily due to Brazil's history of frequently changing exchange rate regimes and the constant fluctuation of exchange rate levels, marked by cycles of appreciation and depreciation. This volatility is especially notable in the context of Brazil's trade with the United States, its second most significant trade partner. Over the years, the trade balance between Brazil and the USA has steadily deteriorated, adding another layer of complexity to the analysis.

For decades, studies in this field have often employed time-invariant methodologies, allowing for asymmetrical effects, or merely distinguishing between long-run and short-run impacts. However, such approaches prove limited when applied to emerging economies, which are susceptible to internal and external shocks, leading to shifts in the macroeconomic panorama (Silva, 2022). A static analysis may fail to account for dynamic factors such as "changes in taste, technology, or economic policies" (Bierens & Martins, 2010), underscoring the need for more adaptable methodologies in studying these economies.

As previously highlighted, Brazil's status as an emerging market makes it a truly unique laboratory for economic analysis. Consequently, it demands a methodology capable of accommodating the changes and disruptions inherent in its economic cycles. One such approach is the time-varying cointegration method proposed by Bierens and Martins (2010), whose interpretation is like Johansen's (1988) cointegration but allows for smooth changes over the time frame analyzed.

In Brazilian economic research, a significant disparity in results arises from the varying levels of aggregation employed. Older studies tend to favor an aggregated approach (Lobo, 2007; Mendes & Piza, 2007; Vasconcelos, 2010; Serdar & Hakan, 2017; Azevedo et al., 2023; Gomes & Paz, 2005; Parray et al., 2023). Conversely, some researchers choose to disaggregate the economy into sectors (Sonaglio, Scalco, & Campos, 2010; Arruda, Brito, & Castelar, 2022; Bahmani-Oskooee, Harvey, & Hegerty, 2014; Ramos Filho & Ferreira, 2016; Ribeiro, Vasconcelos, & Silva, 2021; Arruda & Martins, 2020), adopting various approaches ranging from analyzing isolated sectors like agriculture to segmenting the economy into numerous industries, which may result in complexity and confusion. Additionally, a few studies opt for broader sector classifications, such as industrial and basic products, while only Ramos Filho and Ferreira (2016) and Ribeiro, Vasconcelos, and Silva (2021) specifically examine by technological intensity.

Building on the insights from the preceding discussion, this study proposes to apply the time-varying methodology developed by Bierens and Martins (2010) to the Brazilian economy with a novel approach to disaggregation. This approach will categorize sectors based on their technological intensity, acknowledging the significant role of real exchange rates (RER) in shaping the technological composition of exports, as highlighted by Cimolli, Fleitas, and Porcile (2013). Furthermore, empirical evidence suggests that sectors with greater differentiation are more responsive to exchange rate movements compared to homogeneous ones (Colacelli, 2009). Through this methodology, the study aims to offer a nuanced understanding of the relationship between real exchange rates and sectoral dynamics within the Brazilian economy.

Including this introduction, this work has five sections. Section two presents the theoretical base and empirical works. Section three shows the database and the econometric strategy used. Section four is reserved for the discussion of the results. The fifth section presents the concluding remarks.

2. Literature Review

2.1 Theoretical Literature

Bickerdike (1920), Marshall (1923), Lerner (1944), Robinson (1947), and Metzler (1948) developed a model to elucidate the trade balance, grounded in the elasticities of supply and demand. This model considers two markets: an internal market, where domestic products are demanded by the rest of the world, and an external market, where the domestic country demands products from the rest of the world.

A real depreciation in the exchange rate signifies a reduction in external output and an increase in internal output. This leads to a rise in the value of internal exports as they become more affordable in the external market. However, the impact on imports varies depending on the price elasticity of supply—they may become cheaper or more expensive. The sufficiency condition for a surplus in the trade balance following depreciation is that the derivative concerning the exchange rate must be positive. This condition is known as the Bickerdike-Robinson-Metzler (BRM) Condition.

In response to real depreciation, there is increased consumption of domestic production due to higher import

prices. Simultaneously, the rise in domestic consumption leads to an increase in imports, influenced by the marginal propensity to consume and the price elasticity of external supply. The former effect is called the substitution effect, while the latter is the income effect (Moura & Da Silva, 2005).

Arruda, Castelar, and Martins (2019) represent the BRM Condition through Equation (1), where B represents the trade balance, X and M denote exports and imports in the domestic economy, and Px and Pm signify the prices of exports and imports in domestic currency.

$$B = P_X X - P_M M \tag{1}$$

The BRM model employs total differentiation of Equation (1), where the variation in the trade balance depends on the elasticity of demand for imports and the elasticity of supply for exports (Arruda, Castelar, & Martins, 2019). By understanding these elasticities, one can ascertain whether the income effect outweighs the substitution effect following exchange rate depreciation (Moura & Da Silva, 2005).

Regarding the J-Curve phenomenon, it does not negate the validity of the BRM condition, which pertains to the long run. The J-Curve represents a short-run condition resulting from rigidities that impede immediate improvements in a country's trade balance. "Although prior contracts or earlier purchase orders remain fixed, price changes have an immediate impact following depreciation. Consequently, a decrease in the value of net export earnings leads to a short-term deterioration in the trade balance" (Parray et al., 2023).

Essentially, the J-Curve occurs when the income effect surpasses the substitution effect in the short run. However, with necessary adjustments, the substitution effect prevails over the income effect in the long run if it is indeed greater (Moura & Da Silva, 2005).

2.1 Empirical Evidence

Recent literature in the field has made significant strides in analyzing the Marshall-Lerner condition, particularly focusing on countries that have traditionally received less attention in broad studies. Mehmetaj (2022), for instance, examines the validity of this condition in Albania, particularly in light of the before-and-after effects of the coronavirus pandemic. Ho, Nguyen, and To-The (2023) investigate the applicability of the condition to US-Vietnam trade dynamics, noting its fulfillment only under symmetrical model assumptions, albeit with observed asymmetries upon sectoral disaggregation. In a study focusing on Nigeria, South Africa, and China, Ogbonna, Gbadebo, and Ibenta (2020) find evidence supporting the Marshall-Lerner condition solely for China. Meanwhile, Barkat, Jarallah, and Alsamara (2024) contribute to this discourse by presenting evidence supporting the existence of the Marshall-Lerner condition within the Gulf Cooperation Council (GCC) countries.

Another emerging theme in the literature involves examining the impact of exchange rate volatility on trade balance. Lal, Kumar, Pandey, Rai, and Lim (2023) assert that this volatility affects exporters, sectors, and regions differently, highlighting its nuanced impact. Bosupeng, Naranpanawana, and Su (2024) contribute to this discourse by demonstrating that, generally, volatility diminishes the positive effects of an appreciation shock on the trade balance in developed countries, both in the short and long term. Meanwhile, Kayani, Aysan, Gul, Haider, and Ahmad (2023) explore the linear and non-linear relationships between exchange rate volatility and trade balance across Pakistan, Malaysia, South Korea, and Japan. They discover that while reduced volatility benefits Pakistani and Malaysian exports, it detrimentally affects Japanese exports, showcasing the complexity of this relationship.

In addition to these trends, there have been notable advancements in employing more sophisticated methodologies within empirical literature. Geldner (2024), for instance, investigates the dynamics of G10 and BRICS countries, revealing that advanced economies exhibit short-term J-curve effects, while emerging markets demonstrate price and quantity effects. This analysis is facilitated through the application of nonlinear quantile regression methodology, allowing for a nuanced understanding of the diverse responses across different economic contexts.

Similarly, Felipe, Pérez-Montiel, and Ozcelebi (2024) contribute to methodological innovation by employing time and frequency-domain causality tests. These tests are adept at handling inherent nonlinearity and structural changes within time series data, offering a robust framework for evaluating the relationship between exchange rates and trade balances in selected European countries.

This second part of this section summarizes empirical research on the relationship between exchange rates and Brazilian foreign trade, with a focus on studies utilizing non-linear methods, sectoral approaches, or those highlighting the technological aspect.

Ribeiro, Vasconcelos, and Silva (2021) employ asymmetric regression to analyze the relationship between

exchange rates and exports across 700 categories of the Harmonized System (HS). Their findings reveal an asymmetric effect of exchange rate depreciation on exports, with outcomes varying across HS categories. Despite the majority exhibiting a positive effect, certain sectors benefit more from exchange rate appreciations, particularly those with higher technological intensity.

Arruda and Martins (2020) adopt a panel method for Brazilian states, categorizing products into basic and manufactured goods, as well as total products. They conclude that the J-Curve phenomenon is not applicable to basic products but holds for manufactured goods and total products. Additionally, the Marshall-Lerner (ML) condition is valid, although more prominently for manufactured goods.

Sonaglio, Scalco, and Campos (2010) utilize a vectorial model to examine the occurrence of the ML condition and J-Curve across 21 manufacturing sectors in Brazil-USA trade from 1994 to 2007. They identify evidence of the ML condition in six sectors and the J-Curve in only two.

Ramos Filho and Ferreira (2016) investigate the J-Curve for 19 manufacturing sectors of the Brazilian industry. Employing both long-run and short-run approaches, they find no sectors exhibiting simultaneous effects in both time frames. They note four sectors with incomplete J-Curves and one with an incomplete and inverse J-Curve (shipbuilding and repair), with no evidence of a relationship between the incomplete J-Curve occurrence and technological intensity.

Bahmani-Oskooee, Harvey, and Hegerty (2014) study the J-Curve in Brazil-USA trade, disaggregating trade flows across 92 industries. They identify evidence of the J-Curve in 31 sectors.

Arruda, Brito, and Castelar (2022) investigate the relationship between real exchange rate depreciation and the trade balance for Brazil, disaggregating trade flows into major economic categories, that is, capital goods, durable consumer goods, semi-durable and non-durable consumer goods, intermediate goods, and fuels and lubricants. They find that except for fuels and lubricants, real devaluations have positive and elastic effects on the trade balance.

Branco (2024) examines the short-run relationship between the real exchange rate (RER) and the Brazilian exports basket, disaggregated by technological intensity level, utilizing a NARDL model. Non-linearity is confirmed across all technological intensity categories, with the high-tech industry benefitting more from exchange rate appreciations than depreciations.

Parray et al. (2023) investigate the J-Curve for the BRICS group using a panel method allowing for asymmetry. They find that real exchange rate appreciation deteriorates the trade balance more than devaluation aids it, with no evidence of a J-Curve.

Serdar and Hakan (2017) study the J-Curve for Brazil-USA trade flows using vectorial and neural networks methods. They find no evidence of the J-Curve and argue that real exchange rate devaluations do not benefit the Brazilian trade balance.

Azevedo et al (2023) employ time-varying cointegration to examine the relationship between the real exchange rate and trade balance, focusing solely on the Brazilian agricultural sector. They find an elastic effect of the exchange rate on the trade balance throughout the 2000-2019 period.

The technological dimension of exports is a significant topic of interest, particularly in the context of discussions surrounding export competitiveness. Bournakis (2014) underscores the importance of economic complexity in enhancing export competitiveness. Consequently, there is a growing interest in understanding the linkage between technology and movements in exchange rates, as technological advancements often play a crucial role in shaping a country's export landscape.

Colacelli (2009) conducts an extensive investigation into the relationship between exchange rate variations and exports, disaggregating countries by development and sectors by differentiation, using panel data from 136 countries spanning from 1981 to 1997. The author observes that differentiated sectors respond more to exchange rate fluctuations, especially when developed countries are included in the sample.

Cimolli, Fleitas, and Porcile (2013) investigate the role of the real exchange rate in the diversification of a country's export basket concerning technological intensity, utilizing panel data from 111 countries from 1962 to 2008. They argue that a high Real Exchange Rate (RER) may facilitate the upgrading of export structures towards innovation-intensive products, while an appreciated RER discourages the production of tradable goods.

In summary, while advancements have been made in disaggregating trade flows, results remain heterogeneous. Some studies identify evidence of a J-Curve, while others do not. Generally, when trade flows are disaggregated by industry or sector, results tend to indicate the presence of the J-Curve and ML condition in some sectors.

However, many studies either analyze numerous industries or aggregate them into broad categories.

This paper seeks to contribute by adopting a technological intensity approach to aggregation, as recent research indicates that technological intensity significantly shapes the exchange rate's impact on trade flows. Additionally, the paper employs a time-varying cointegration strategy, which is crucial for application in emerging economies susceptible to cyclical fluctuations in economic activity and internal and external shocks.

3. Methodological Aspects

3.1 Classification by Technological Intensity (CTI)

The categorization of Brazilian exports and imports by technological intensity is not native in the Brazilian foreign trade databases. However, MDIC (2020) provides a methodology in its manual for grouping sections of the Harmonized System (HS) based on the Mercosur Common Nomenclature (NCM) into technological intensity categories.

This procedure aligns with the methodology outlined by OECD (2015), which involves converting HS codes into the International Standard Industrial Classification of All Economic Activities (ISIC) classification from the United Nations. Subsequently, the ISIC categories are grouped into four technological categories: High Tech, Medium-High Tech, Medium-Low Tech, and Low Tech.

The sectors which are grouped in each category can be found in the Chart 1 of the OECD (2015) documentation. For instance, in the High-Tech classification, sectors such as aircraft, electronic and optical products, and pharmaceutical products are included. In the Medium-High Tech category, sectors like electrical materials, motor vehicles, chemical, railway and transport equipment, and machinery and equipment are listed. The Medium-Low category encompasses sectors like shipbuilding, rubber and plastic, coke, refined petroleum and nuclear fuel, non-metallic, basic metallurgy, and metallic products. Finally, the Low Technology classification includes sectors such as wood, paper and cellulose, editorial and illustration, food, beverages and tobacco, textiles and clothing, and leather and footwear.

Chart 1. Classification of the Industry by Technological Intensity

High Tech
Aircraft and spacecraft
Computer equipment, electronic and optical products
Pharmachemical and Pharmaceutical Products
Medium-high Tech
Chemicals
Electrical machines, apparatus and materials
Machines and equipment
Motor vehicles, trailers and bodies
Railway vehicles and transport equipment
Military and combat vehicles
Medium-low Tech
Coke, petroleum products and biofuels
Non-metallic mineral products
Metallurgy and metal products, except machinery and equipment
Naval vessels
Low Tech
Food, beverages and tobacco
Textiles, leather and footwear
Pulp, paper and printing
Wood and its products
Furniture and other manufactures

3.2 Dataset

To estimate the dynamic elasticities of the trade balance considering the technological intensity classification (CTI), we utilize monthly data spanning from January 2000 to December 2022 and employ the time-varying error correction vector modeling (VECM-TVC) proposed by Bierens and Martins (2010). A descriptive summary of the variables used, and their respective sources is presented in Chart 2.

The trade balance indicator is derived from the natural logarithm of the ratio between Brazilian exports and imports, a common configuration for this variable in the empirical literature (Moura & da Silva, 2005; Sonaglio, Scalco, & Campos, 2010; Azevedo et al., 2023). This variable is constructed using data on exports and imports of high-tech, medium-high tech, medium-low tech, and low-tech goods, following the CTI classification. These data are sourced from the ComexStat Database, provided by the Brazilian Ministry of Development and Foreign Trade (MDIC).

The Real Exchange Rate (RER) indicator, obtained from the Time Series Generator System of the Central Bank of Brazil (BCB-SGS), represents a weighted geometric average of the economy's largest trading partners. It considers the Wholesale Price Index - Internal Availability (IPA-DI), which solely assesses tradable goods.

Chart 2. Summary of the variables used

Variable	Proxy	Period	Source
Real Exchange Rate (RER)	Natural logarithm of the effective real exchange rate	01/2000- 12/2022	BCB-SGS
Domestic Income	Natural logarithm of Brazil's monthly GDP	01/2000- 12/2022	BCB-SGS
Foreign income	Natural logarithm of world imports	01/2000- 12/2022	DOTS-FMI
Commercial Balance of High-Tech Goods	Natural logarithm of the commercial balance of high tech goods	01/2000- 12/2022	MDIC
Commercial Balance of Medium-High Tech Goods	Natural logarithm of the commercial balance of medium-high tech goods	01/2000- 12/2022	MDIC
Commercial Balance of Medium-Low Tech Goods	Natural logarithm of the commercial balance of medium-low tech goods	01/2000- 12/2022	MDIC
Commercial Balance of Low-Tech Goods	Natural logarithm of the commercial balance of low tech goods	01/2000- 12/2022	MDIC

Source: Own elaboration.

The proxy for domestic income is the monthly GDP of Brazil, sourced from the Central Bank of Brazil (BCB), and deflated by the General Price Index – Internal Availability (IGP-DI). Meanwhile, the proxy for external demand comprises total world imports in current dollars CIF (Cost, Insurance, and Freight), obtained from the Direction of Trade Statistics (DOTS) by the International Monetary Fund (IMF). These values are deflated by the price index of total world imports, available in the Federal Reserve Economic Data of St. Louis (FRED).

Figure 1 illustrates the evolution of exports and imports across CTI levels. It is evident that the low-tech sectors are the best-performing ones in Brazil. In terms of imports, medium-high tech sector surpasses those of high-tech due to the greater significance of these activities.

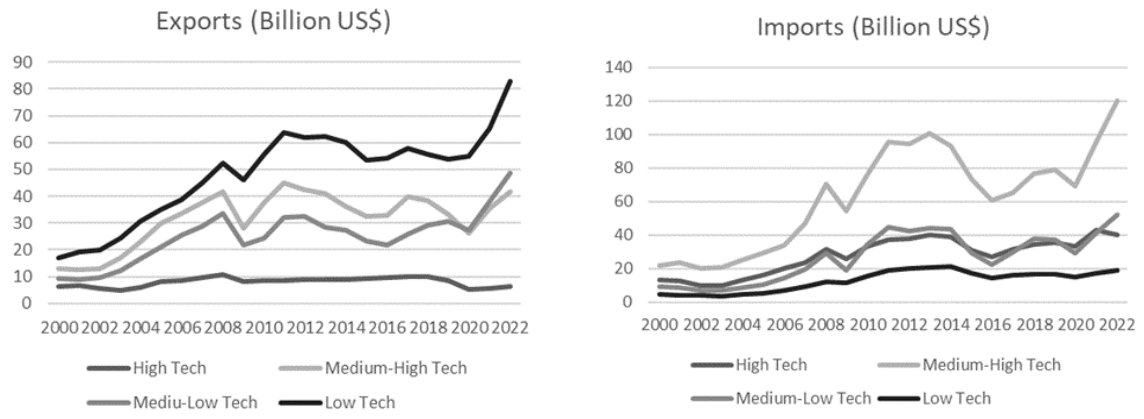

Figure 1. FOB Exports and Imports CTI (billion US$)

Figure 2 displays the trade balance by CTI level. It is evident that the only sector consistently achieving surpluses is the low-tech sector. Meanwhile, the medium-low tech sector exhibits both surpluses and deficits. Importantly, deficits in the medium-high tech sector outweigh those in the high-tech sector due to its greater participation for the Brazilian trade.

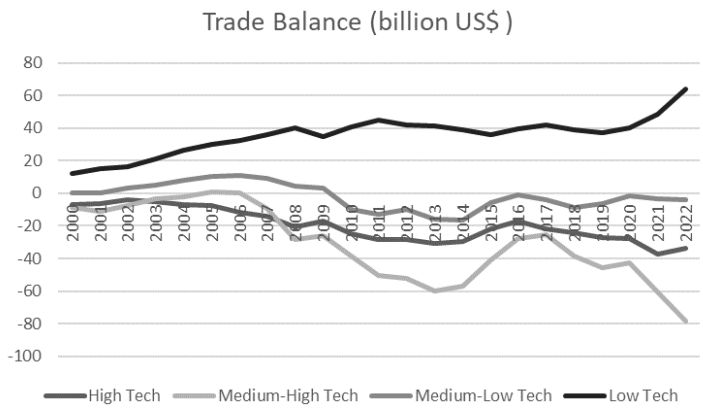

Figure 2. FOB Trade Balance by Technological Intensity Level (Billion US$)

In Table 1, the share of each CTI sector in Brazilian exports and imports is presented. Observing exports, it's evident that the high-tech sector has been progressively losing its share, while the uncategorized sector (agriculture and commodities) has consistently grown to represent almost half of the export basket. Regarding imports, there is a persistent dependence on the high and medium-high technology sectors.

Table 1. Share of Brazilian exports and imports by CTI (%)

	High Tech		Medium-High Tech		Medium-Low Tech		Low Tech		Uncategorized	
	EXP	IMP	EXP	IMP	EXP	IMP	EXP	IMP	EXP	IMP
2000	11.9	23.2	23.7	38.6	16.7	15.8	31.0	8.4	16.6	13.9
2001	11.5	22.4	21.7	41.8	15.3	15.0	33.4	7.4	18.1	13.4
2002	9.3	19.9	21.6	42.0	16.4	14.1	33.5	7.8	19.2	16.2
2003	6.5	19.7	23.3	41.3	16.7	13.9	33.6	7.2	19.9	17.9
2004	6.5	20.9	23.9	39.5	17.4	13.7	32.2	6.8	20.0	19.2
2005	7.0	21.6	25.1	38.7	17.8	14.1	29.5	6.8	20.6	18.7
2006	6.4	21.8	24.5	36.5	18.6	15.6	28.3	7.2	22.3	18.9
2007	6.0	19.4	23.7	38.7	17.9	16.1	28.0	7.4	24.4	18.3
2008	5.5	18.0	21.2	40.2	17.2	16.7	26.7	7.0	29.4	18.1
2009	5.5	19.8	18.5	42.0	14.4	14.5	30.3	8.7	31.3	15.0
2010	4.2	18.2	18.8	41.5	12.2	18.8	27.8	8.3	36.8	13.2
2011	3.4	16.3	17.7	41.9	12.6	19.6	25.2	8.3	41.1	13.9
2012	3.8	16.7	17.7	42.0	13.5	18.8	25.8	8.8	39.3	13.6
2013	3.8	16.5	17.6	41.8	12.3	18.3	26.7	8.5	39.5	14.9
2014	4.1	16.8	16.4	40.4	12.3	19.0	27.1	9.1	40.0	14.8
2015	4.9	17.8	17.4	42.2	12.6	17.0	28.6	10.0	36.5	12.9
2016	5.5	19.2	18.3	43.4	12.2	16.2	30.1	10.3	33.8	10.8
2017	4.6	20.0	18.5	41.1	12.0	18.7	26.9	10.1	38.1	10.1
2018	4.4	18.7	16.5	41.4	12.6	20.5	23.9	9.1	42.5	10.4
2019	3.9	19.2	15.1	42.4	13.9	20.0	24.3	8.9	42.9	9.5
2020	2.6	20.8	12.6	43.5	13.2	18.4	26.3	9.3	45.4	8.0
2021	2.0	19.6	12.6	43.7	13.6	18.9	23.2	7.7	48.7	10.1
2022	1.9	15.3	12.6	45.8	14.6	19.9	25.0	7.2	46.0	11.9

Source: Own elaboration.

3.3 Econometric Strategy

A log-log model, represented by Equation (2), is estimated to analyze the relationship between the real exchange rate and the trade balance, defined as the ratio between the values of exports and imports, which is a commonly utilized format in the literature for each CTI sector.

$$ln\left(\frac{X_t}{M_t}\right) = \beta_o + \beta_1\, ln(RER_t) + \beta_2\, ln(Y_t) + \beta_3\, ln(Y_t^*) + \varepsilon_t \quad (2)$$

Where: $ln(X_T/M_T)$ represents the natural logarithm of the exports/imports ratio for high-tech, medium-high

tech, medium-low tech, and low-tech goods; $ln(RER_t)$ denotes the natural logarithm of the effective real exchange rate; $ln(Y_t)$ indicates the natural logarithm of the real domestic income; $ln(Y_t^*)$ signifies the natural logarithm of the real income of rest of the world; $\beta_o, \beta_1, \beta_2, \beta_3$ represent parameters to be estimated and ε_t represents the error term.

Although Johansen's (1988) cointegration technique is commonly used, as highlighted in previous sections, one of the distinguishing features of this study is the utilization of a cointegration method that allows for time variation. This approach is deemed more suitable for developing economies that experience frequent changes in the macroeconomic scenario.

We adopt the methodology proposed by Bierens and Martins (2010), which introduces a cointegration approach where long-term relationships can vary smoothly over time using orthogonal Chebyshev polynomials. It's worth noting that Johansen's (1988) methodology is a particular case of this model.

Therefore, we employ a modified version of vector autoregression (VAR) in the form of error correction, as outlined by Bierens and Martins (2010). This approach facilitates the consideration of multiple cointegration relations (VECM-TVC) and is represented by the model:

$$\Delta Y_t = \mu + \Pi_t' Y_{t-1} + \sum_{j=1}^{p-1} \Gamma_j \Delta Y_{t-j} + \varepsilon_t \tag{3}$$

in which, μ is the vector of intercepts, fixed over time, Y_t is a vector of observations for each time serie in time t, Γ_j, $j = 1, \dots p$ are vectors of coefficients of ΔY_{t-j}, Π_t' is the matrix that presents the long-run relationship, which varies over time, and ε_t is the error vector, so that $\varepsilon_t \sim i.i.d\ N_k\ [0, \Omega]$.

The intention is to test the null hypothesis of time invariant cointegration (TIC) $\Pi_t' = \Pi' = \alpha\beta'$, in which α and β are fixed matrices k x r, against the hypothesis of time varying cointegation (TVC), $\Pi_t' = \alpha\beta_t'$, with rank $(\Pi_t') = r < k$, for $t = 1, \dots, T$, with fixed α, and β_t's are k x r time-varying matrices with constant rank r. Bierens and Martins (2010) define the Chebyshev polynomials as:

$$P_{0,T}(t) = 1, \quad P_{i,T}(t) = \sqrt{2}\cos\left(i\pi\frac{(t-0,5)}{T}\right) \tag{4}$$
$$t = 1, \dots, T, \quad i = 1,2,3, \dots,$$

Being t the period, and i the sample element, and the polynomials presenting orthonormality property, it is true for all integers i, j:

$$\frac{1}{T}\sum_{t=1}^{T} P_{i,T}(t)P_{j,T}(t) = 1(i = j) \tag{5}$$

Therefore, any g(t) function of discrete time t=1,…,T, can be represented by:

$$g(t) = \sum_{i=0}^{T-1} \xi_{i,T} P_{i,T}(t), \textit{where } \xi_{i,T} = \frac{1}{T}\sum_{t=1}^{T} g(t)P_{i,T}(t) \tag{6}$$

g(t) can be decomposed in components of $\xi_{i,T}P_{i,T}(t)$, which smoothly decrease, so that it can be approximated by:

$$g_{m,T}(t) = \sum_{i=0}^{m} \xi_{i,T} P_{i,T}(t) \tag{7}$$

for some fixed natural number m<T-1.

Therefore, the variability of β_t over time can be obtained through the expansion in terms of these polynomials, for some fixed m order:

$$\beta_t = \beta_m\left(\frac{t}{T}\right) = \sum_{i=0}^{m} \xi_{i,T} P_{i,T}(t) \tag{8}$$

Similarly to Johansen (1988), the estimation is done by Maximum Likelihood, but, with the introduction of Chebyshev temporal polynomials. That way, we substitute $\Pi_t' = \alpha\beta_t' = \alpha\left(\sum_{i=0}^{m} \xi_{i,T} P_{i,T}(t)\right)'$ in equation (3):

$$\Delta Y_t = \mu + \alpha\left(\sum_{i=0}^{m} \xi_{i,T} P_{i,T}(t)\right)' Y_{t-1} + \sum_{j=1}^{p-1} \Gamma_j \Delta Y_{t-j} + \varepsilon_t \tag{9}$$

The authors propose a likelihood ratio test for the equation (9), LR_T^{tvc}, for investigating the null hypothesis of TIC, which means that the estimated parameters of the Chebyshev polynomial are jointly zero. Given m and r, the LR_T^{tvc} test statistic becomes:

$$\Delta LR_T^{tvc} = -2\left[\hat{l}_T(r,0) - \hat{l}_T(r,m)\right] = T\sum_{j=1}^{r} \ln\frac{1-\hat{\lambda}_{0,j}}{1-\hat{\lambda}_{m,j}} \tag{10}$$

In short, we begin by the usual unity root tests; in case of non-stationarity, the cointegration analysis procedures from Johansen (1988) are performed, by the statistics of the trace and maximum eigenvalue. If there is cointegration, the likelihood test for TVC from Bierens and Martins (2010) is performed. If the null hypothesis is

rejected, the dynamic elasticities are estimated.

4. Analysis of the results

Firstly, the order of integration of the series is analyzed through ADF and KPSS tests. The results, which consider a level of significance of 5%, are indicated in table 2. All the analyzed series are integrated of order 1, I(1).

Table 2. Results of Unit Root tests

Variable	Specification	ADF	KPSS	Order of Integration
$\ln(Real\ Exchange\ Rate_t)$	Level	-2.07 [-2.87]	0.86 [0.46]	I(1)
	First Difference	-12.87 [-2.87]	0.08 [0.46]	
$\ln(Foreing\ Income_t)$	Level	-2.08 [-2.87]	1.59 [0.46]	I(1)
	First Difference	-4.27 [-2.87]	0.34 [0.46]	
$\ln(Domestic\ Income_t)$	Level	-1.12 [-2.87]	0.58 [0.46]	I(1)
	First Difference	-4.03 [-2.87]	0.29 [0.46]	
$\ln(High-tech\ trade\ balance_t)$	Level	-1.41 [-2.87]	1.39 [0.46]	I(1)
	First Difference	-4.08 [-2.87]	0.08 [0.46]	
$\ln(Medium-high\ tech\ trade\ balance_t)$	Level	-1.38 [-2.87]	1.10 [0.46]	I(1)
	First Difference	-3.10 [-2.87]	0.14 [0.46]	
$\ln(Medium-low\ tech\ trade\ balance_t)$	Level	-2.38 [-2.87]	0.92 [0.46]	I(1)
	First Difference	-12.65 [-2.87]	0.14 [0.46]	
$\ln(Low-tech\ trade\ balance_t)$	Level	-1.59 [-2.87]	0.89 [0.46]	I(1)
	First Difference	-3.40 [-2.87]	0.12 [0.46]	

Source: Own elaboration.

Table 3 presents the results of the trace and maximum eigenvalue tests conducted for each model. Both tests indicate the presence of cointegration. In Table 4, we utilize the methodology proposed by Bierens and Martins (2010) to examine the presence of time-varying cointegration. The null hypothesis of the likelihood ratio test assumes the existence of time-invariant cointegration. The effectiveness of the test relies on the order, m, of the polynomial. To determine the appropriate order m of the polynomial, we employed the usual information criteria following the approach outlined by Bierens and Martins (2010).

Table 3. Trace and Maximum eigenvalue tests

Test Structure		Eigenvalue	Trace Statistic	Trace Test Critical Value	P-value	Maximum Eigenvalue Statistic	Maximum Eigenvalue Critical Value	P-value
H0	H1							
High-tech model								
r=0	r≥1	0.12	71.23	47.85	0.01	45.93	27.58	0.01
r≤1	r≥2	0.07	16.02	29.79	0.65	11.35	21.13	0.61
Medium-high tech model								
r=0	r≥1	0.14	61.45	47.85	0.00	42.80	27.58	0.00
r≤1	r≥2	0.04	18.65	29.79	0.51	12.34	21.31	0.51

Medium-low tech model								
r=0	r≥1	0.10	51.73	47.85	0.02	31.13	27.58	0.01
r≤1	r≥2	0.04	20.60	29.79	0.38	13.32	21.13	0.42
Low-tech model								
r=0	r≥1	0.11	52.31	47.85	0.01	33.32	27.58	0.00
r≤1	r≥2	0.04	18.99	29.79	0.49	12.61	21.13	0.48

Source: Own elaboration.

Table 4. Bierens and Martins (2010) test for time-varying cointegration

Model	Likelihood Ratio Statistics	Order of Chebyshev polynomial (m)
High-tech trade balance	46.59 [0.00]	m=2
Medium-high tech trade balance	80.01 [0.00]	m=3
Medium-low tech trade balance	37.58 [0.00]	m=3
Low-tech trade balance	66.08 [0.00]	m=2

Source: Own elaboration.

The tests suggest rejection of the null hypothesis, indicating that Johansen cointegration models need to be augmented with Chebyshev temporal polynomials to accurately model the long-term relationships. Consequently, we proceed with the estimation of dynamic elasticities for each CTI model: High Tech, Medium-High Tech, Medium Low Tech, and Low-Tech.

Table 5 presents the descriptive statistics, and Figure 3 illustrates the long-run dynamic elasticities for the high-tech model. A notable observation is the symmetry between the elasticities of domestic and foreign incomes. While both assume negative and positive values, there is a tendency for one to become positive when the other becomes negative, and vice versa. Regarding the Real Exchange Rate (RER) elasticity, it consistently maintains a negative value throughout the analyzed period, fluctuating between less and more negative values. Therefore, we can affirm that the Marshall-Lerner Condition is not valid for the high-tech model. Three distinct time periods can be delineated: 2000-2004, during which period, the average RER elasticity is -0.46; 2005-2016, in which timeframe, the average RER elasticity is -0.28, and 2017-2022, during which period, the average RER elasticity is -1.43.

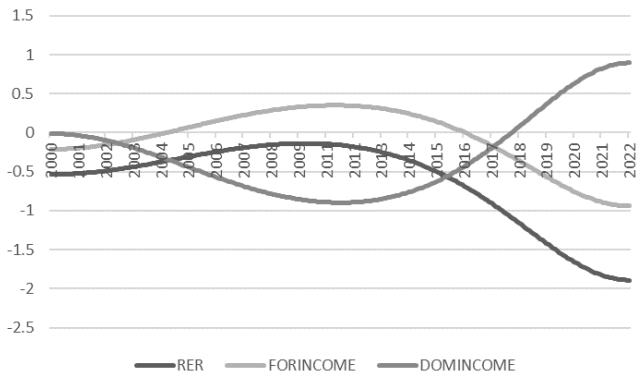

Figure 3. Long-run dynamic elasticities for the high-tech model

The period considered most "normal," spanning from 2005 to 2016, falls between the recovery from the Asian debt crisis, which significantly impacted Brazil, and the Brazilian impeachment crisis, which brought about institutional instability. These events likely had a pronounced effect on high-tech industries in Brazil. From 2017 onwards, a reversal in the external and internal income elasticities is observed, accompanied by a progressive increase in the negativity of the Real Exchange Rate (RER) elasticity. This trend is likely attributed to Brazilian high-tech industries relying heavily on imported inputs. The inversion in income elasticities signals suggests that, amidst exchange rate depreciation, Brazilian consumers experienced a reduction in purchasing power, leading to a shift from external goods to domestic ones. However, domestic goods faced reduced competitiveness

internationally due to the higher costs of inputs.

This result is pretty much consistent with what Ribeiro, Vasconcelos and Silva (2021) had found about sectors more intensive in technology being benefited by exchange rate appreciation. It is also consistent with Branco's (2024) estimations that high-tech trade balance benefits more from exchange rate appreciations than from depreciations.

Table 5. Descriptive statistics of the dynamic elasticities in the High-tech model

Variables	Average	Standard Deviation	Amplitude	
			Maximum	Minimum
Real Exchange Rate	- 0.62	0.53	-0.13	-1.89
Foreign income	-0.06	0.37	0.35	-0.94
Domestic Income	-0.29	0.52	0.89	-0.89

Source: Own elaboration.

Table 6 presents the descriptive statistics, and Figure 4 illustrates the long-run dynamic elasticities for the medium-high tech model. Once again, there is symmetry between the dynamic elasticities of external and domestic incomes. Overall, the elasticity of domestic income is negative, except for the period from 2004 to 2007, during which it slightly surpasses zero (reaching a maximum of 0.07). In contrast, the elasticity of foreign income remains consistently positive throughout the entire period.

Regarding the Real Exchange Rate (RER) elasticity, it can be inferred that the Marshall-Lerner condition is not satisfied. The elasticity oscillates between positive and negative values throughout the entire period, but the overall average, as shown in Table 6, is negative at -0.51. Four distinct periods can be delineated: 2000-2004, the average RER elasticity is -0.72; 2005-2010, the average RER elasticity is 0.29; 2011-2019, the average RER elasticity is -1.27, and 2020-2022, the RER elasticity increases to 0.58.

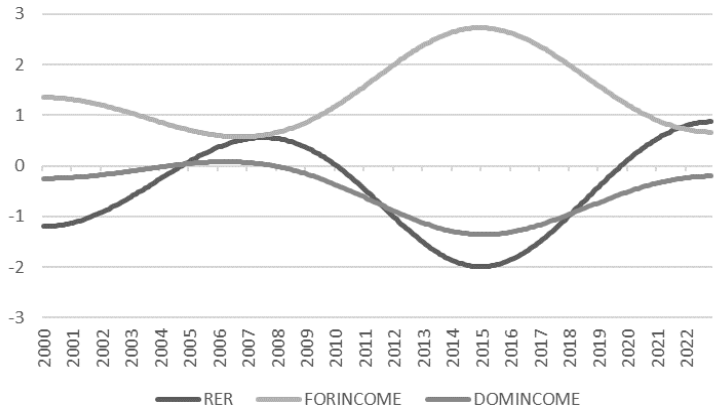

Figure 4. Long-run dynamic elasticities for the medium-high tech model

The changes in the Real Exchange Rate (RER) elasticity for medium-high tech industries compared to high-tech industries are notable. Not only is the RER elasticity much more volatile for medium-high tech industries, but it also increases in the latter years of the sample, as opposed to decreasing further. This trend suggests that medium-high tech industries may not rely as heavily on imported inputs as high-tech industries do. Consequently, when the real exchange rate depreciates, medium-high tech industries become more competitive, leading to an increase in the RER elasticity. This implies that they are better positioned to withstand fluctuations in the exchange rate and may even benefit from real depreciation in certain circumstances.

Table 6. Descriptive statistics of the dynamic elasticities in the medium-high tech model

Variables	Average	Standard Deviation	Amplitude	
			Maximum	Minimum
Real Exchange Rate	- 0.51	0.87	0.86	-1.99
Foreign income	1.42	0.71	2.72	0.56
Domestic Income	-0.50	0.48	0.07	-1.36

Source: Own elaboration.

The descriptive statistics and the graphic of the long-run dynamic elasticities for the medium-low tech model are exhibited in table 7 and figure 5, respectively. Following the conventional expectation, the foreign income elasticity is positive, and the domestic income elasticity is negative throughout all the time analyzed.

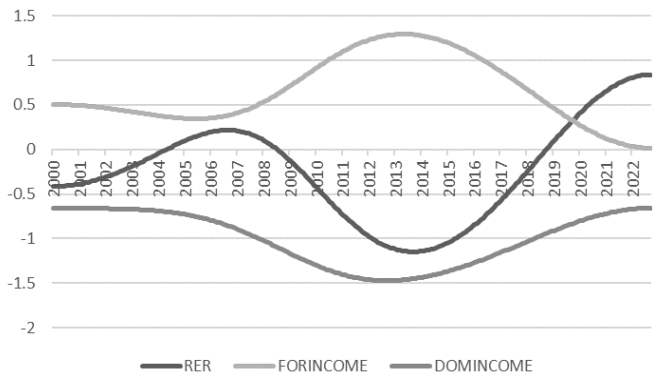

Figure 5. Long-run dynamic elasticities for the medium-low tech model

Regarding the RER dynamic elasticity, it is like the medium-high tech model one. Four distinct periods can be delineated: in the period from 2000 to 2004, the average RER elasticity is -0.23; from 2005 to 2009, it increases to 0.07; during the span of 2010 to 2018, the average RER elasticity declines to -0.77; finally, from 2019 to 2022, the RER elasticity rises to 0.53.

Table 7. Descriptive statistics of the dynamic elasticities in the medium-low tech model

Variables	Average	Standard Deviation	Amplitude	
			Maximum	Minimum
Real Exchange Rate	-0.24	0.55	0.84	-1.14
Foreign income	0.65	0.38	1.29	0.01
Domestic Income	-1.00	0.29	-0.65	-1.47

Source: Own elaboration.

The descriptive statistics and the graphic of the long-run dynamic elasticities for the low-tech model are exhibited in table 8 and figure 6, respectively. Following the conventional expectation, the domestic income elasticity is negative throughout all the sample time, but, although mostly positive, the foreign income elasticity becomes negative in September 2020 to the end of sample time. This evidence can be explained by the covid 19 pandemic.

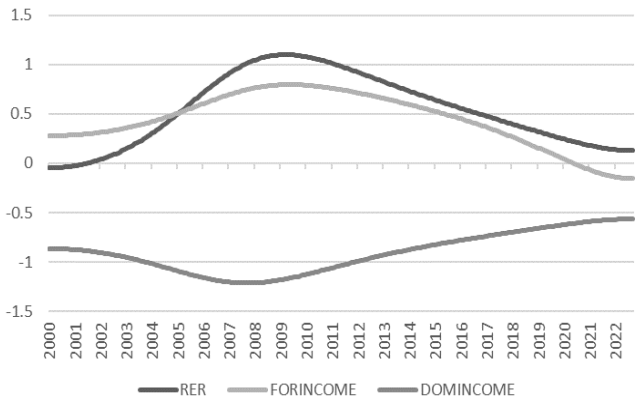

Figure 6. Long-run dynamic elasticities for the low-tech model

Regarding the RER dynamic elasticity, the low-tech model is the best-behaved model. The total average elasticity, as shown in table 8, is 0.54. As most of the sample time this elasticity appears as positive, it can be said that the Marshall-Lerner condition is met. This elasticity shows almost-zero negative results from the beginning of the sample to September 2001. It grew up until 2009, when it reached 1.1, and from 2010 onwards

it only fell, reaching 0.12 in 2022.

The rise in the RER elasticity follows the commodity boom from the 2000s, which was so important to Brazil that maintained its exchange rate consistently appreciating throughout the decade. The peak in 2009 can be safely attributed to the international financial crisis, which weakened the commodities trade.

Although commodities are not considered in the CTI, they play an important part in the added value and comparative advantage of low-tech industry. Similarly to the results obtained for the low-tech industry, Azevedo et al. (2023) obtain a positive elasticity of Brazilian agricultural exports to the RER during practically all the studied period, using the same methodology.

Table 8. Descriptive statistics of the dynamic elasticities in the low-tech model

Variables	Average	Standard Deviation	Amplitude	
			Maximum	Minimum
Real Exchange Rate	0.54	0.36	1.10	-0.04
Foreign income	0.43	0.27	0.79	-0.15
Domestic Income	-0.90	0.20	-0.56	-1.21

Source: Own elaboration.

On an aggregate level, considering all the sectors, it could be said that the Marshall-Lerner condition is not valid, as it was not confirmed for high-tech, medium-high tech and medium-low tech industries, but, considering that these sectors account for less than half of Brazilian exports in the studied period, that might not be the best answer. Despite all that, some recent works find no evidence of Marshall-Lerner condition for the Brazilian economy (Parray et al., 2023; Serdar & Hakan, 2017)

The results agree with works that disaggregate the sectors of the economy, in the sense that the Marshall-Lerner condition is valid only a minority of the sectors. Sonaglio, Scalco, and Campos (2010), from a total of 21 sectors, find Marshall-Lerner evidence for only 6 of them, most of them in the low-tech sector: rubber, footwear, wood, clothing, vehicle parts, and electronic equipment. It's important to notice that, although results are similar to some extent, this is a considerably older work. Bahmani-Oskooee et al. (2014) find Marshall-Lerner evidence only for 31 industries (between 92 in total). Ramos Filho and Ferreira (2016), who carry out a disaggregated study for 19 industries, find no evidence of Marshall-Lerner condition for any sector.

5. Concluding Remarks

The present work attempted to add to the existent literature one more disaggregated in sectors approach to testing the relationship between RER and the Brazilian trade balance, considering technological intensity as the disaggregation factor, as other works have been using very broad categories like "differentiated" and "basic" products, or too many categories, in a way that makes it difficult to borrow assertive conclusions.

For this matter, the adopted econometric strategy is the time-varying cointegration, as it is understood that developing economies face so many external influences on their macroeconomic scenarios that a time-invariant cointegration strategy might not capture their complexity, and that is probably one of the main reasons of why works regarding this relationship for the Brazilian trade balance seem to not agree between themselves.

The technological intensity classification (CTI) groups industries in: High Tech, Medium-High Tech, Medium-Low Tech, Low Tech. The used dataset is composed of monthly information relating to the period between January 2000 and December 2022.

The empirical exercise reveals that the Marshall-Lerner condition is not valid for the High-Tech, Medium-High Tech, and the Medium-Low Tech categories, but only the Low-Tech industry, which, combined with the uncategorized goods (agriculture and commodities), account for more than half of Brazilian exports.

For the High-tech industries, the main conclusion is that the signals of the dynamic elasticities are the opposite of what would be normally expected, and these opposite trends have been strengthening in the last years of the sample. In other words, the foreign income elasticity has been getting more negative, the internal income has been getting more positive and the RER elasticity has been getting more negative. In the current scenario, in which the exchange rate has been depreciating for years and the Brazilian high-tech goods have been losing share in exports, that's probably a consequence of depending too much on imported inputs.

For the medium-high and medium-low technology sectors, the signals of the elasticity oscillate so much over the years that it is difficult to draw assertive conclusions beyond the fact that each major external influence or

internal institutional crisis in Brazil seems to be the driver of changes in the trajectory of elasticities.

Although the RER dynamic elasticity for low-tech sector is majorly positive, it has been diminishing since 2009. It is argued that, due to agriculture and commodities being a great part of the added value in the low-tech industry, this sector might be receiving much influence of the transformations Brazil has been facing in the agricultural sector since the 1990s, as the increasing adoption of imported inputs results in a lower benefit of a devalued exchange rate.

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