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Commodity Prices and the Brazilian Stock Market: Evidence from a Structural VAR Model

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Abstract: Brazil is a resource-rich economy that relies heavily on the exports of several important commodities. The variability of commodity prices affects both the economy and the stock market. This study investigates the relationship between commodity price shocks and stock returns in Brazil using a structural vector autoregressive (SVAR) model. This study uses monthly data on prices of five major export commodities, stock returns, and several control variables, covering the period from January 2010 to December 2022. To account for the Brazilian economic crisis between 2014 and 2016, we have analyzed the effects of commodity prices on stock prices in three different time periods, namely, before the economic crisis (January 2010–March 2014), during the economic crisis (April 2014–December 2016), and after the economic crisis (January 2017–December 2022). The empirical results of this study provide evidence to conclude that stock returns increase following a positive global commodity price shock or a positive exchange rate shock. The effects are more noticeable during the economic crisis in Brazil. The results also show that the volatility of Brazilian stock returns is mostly explained by global oil prices and exchange rate movements in the long run.

Keywords: stock returns; commodity prices; SVAR model; unit root tests; cointegration; Brazil

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1. Introduction

The countries that are heavily dependent on primary commodity exports find that their economies are adversely affected by the fluctuations in commodity prices. Such fluctuations could also affect their stock markets. Primary commodities play an important role in economic development in the world. Understanding the relationship between changes in commodity prices and stock market returns helps us identify and improve portfolio strategies and risk positions. Brazil is a resource-rich and economically dynamic country that depends heavily on exports of a few primary commodities. It is the third-largest economy in the Western Hemisphere. Over the past two decades, Brazil has been consolidating its position as a major producer of agricultural commodities and related food products and has become a major global supplier of commodities such as soybeans, grains, cotton, ethanol, and meats. The value of Brazil's agricultural exports, including processed products, accounts for about 43% of Brazil's total exports.

The COVID-19 pandemic adversely affected the Brazilian economy in 2020 after negative growth in 2014–2019 but experienced a strong rebound in 2021–2022. According to the World Bank (2024) [1], the international commodity boom helped Brazil maintain an average GDP growth rate of about 3.3% per year during the period from 2001 to 2014. The domestic expansion of social programs, among others, also helped Brazil maintain robust economic growth. However, due to the falling commodity prices in combination with political turmoil, the real GDP dropped by −0.3% between 2014 and 2019 and further dropped by −3.3% in 2020 due to the COVID-19 pandemic. As a result of a favorable commodity market, a successful vaccination campaign, and resilient domestic demand, supported by social transfers, among others, economic growth rebounded to 5.0% in 2021 and 2.9% in 2022 and 2023. Figure 1 illustrates the economic growth experience of Brazil during the period from 2001 to 2022.

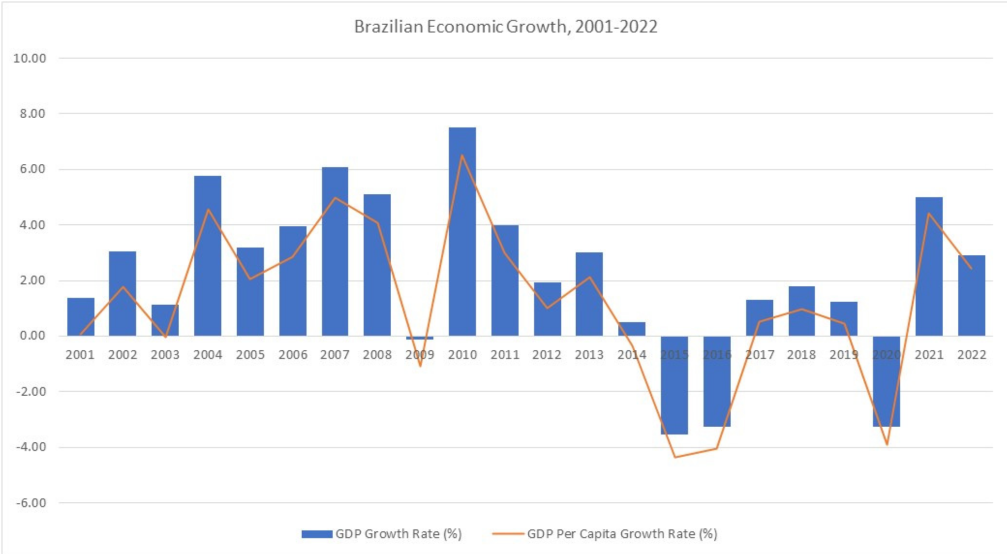

Figure 1. Economic growth in Brazil. Note: The graph is based on data from The World Bank World Development Indicators database 2024 [2].

The major export product categories of Brazil during the period from 2013 to 2022 are presented in Table 1. As the table illustrates, mineral products and vegetable products have remained the two largest export product groups, accounting for nearly 50% of total exports. The export share of both products has increased during this period, indicating their relative importance. Other important product groups include machines, metals, transportation, and animal products.

Table 1. Brazilian exports by major product category, 2013–2022.

Section		Export Value (USD Mns.)			Export Share (Percent)		
ID	Section	2013	2017	2022	2013	2017	2022
1	Animal Products	16,817.4	15,755.3	25,905.1	7.07	7.08	7.60
2	Vegetable Products	37,078.7	37,869.4	72,732.1	15.59	17.02	21.34
3	Animal and Vegetable Bi-Products	2058.2	1539.3	5281.8	0.87	0.69	1.55
4	Foodstuffs	32,154.0	27,231.8	33678.1	13.52	12.24	9.88
5	Mineral Products	54,462.2	42,856.3	92,352.8	22.90	19.27	27.09
6	Chemical Products	12,179.2	11,251.3	14,259.0	5.12	5.06	4.18
7	Plastics and Rubbers	5562.6	5512.6	5984.8	2.34	2.48	1.76
8	Animal Hides	2686.7	2097.4	1357.4	1.13	0.94	0.40
9	Wood Products	2145.3	2937.7	4682.2	0.90	1.32	1.37
10	Paper Goods	8026.6	9227.3	12090.6	3.37	4.15	3.55
11	Textiles	2466.6	2425.1	4921.1	1.04	1.09	1.44
12	Footwear and Headwear	1295.0	1289.6	1513.8	0.54	0.58	0.44
13	Stone And Glass	1992.6	1987.9	2388.5	0.84	0.89	0.70
14	Precious Metals	3725.5	3522.2	5762.5	1.57	1.58	1.69

Table 1. *Cont.*

Section ID	Section	Export Value (USD Mns.) 2013	2017	2022	Export Share (Percent) 2013	2017	2022
15	Metals	14,936.8	16,451.8	20,674.8	6.28	7.40	6.07
16	Machines	17,985.2	17,285.4	17,239.4	7.56	7.77	5.06
17	Transportation	19,709.0	20,412.8	16,919.3	8.29	9.18	4.96
18	Instruments	978.3	1004.2	1057.4	0.41	0.45	0.31
19	Weapons	465.2	690.4	661.8	0.20	0.31	0.19
20	Miscellaneous	992.3	916.1	1226.3	0.42	0.41	0.36
21	Arts and Antiques	124.1	186.4	167.8	0.05	0.08	0.05
	Total All Products	237,841.4	222,450.5	340,856.5	100.00	100.00	100.00

Source: The Observatory of Economic Complexity (OEC) (https://oec.world/en/profile/country/bra (accessed on 30 August 2024)) [3].

In this paper, we contribute to the emerging empirical literature dealing with the relationship between commodity price shocks and stock market returns focusing on a leading commodity-exporting country. The objective of this study is to investigate the relationship between commodity price shocks and stock returns in Brazil, focusing on five primary commodities, namely, petroleum, iron ore, soybeans, poultry, and sugar. In 2022, the value of total exports of Brazil was USD 340.9 billion, and the five major export products of Brazil were soybeans (USD 47.2 billion), crude petroleum (USD 43.1 billion), iron ore (USD 30.1 billion), refined petroleum (USD 12.9 billion), and corn (USD 12.4 billion). They accounted for 13.8%, 12.6%, 8.8%, 3.9%, and 3.6% of total exports, respectively.

Figure 2 illustrates the trends in stock returns, price of petroleum, price of iron ore, price of soybeans, price of poultry, and price of sugar during the period from January 2010 to December 2022. The shaded area in the graph corresponds to the period of economic crisis from April 2014 to December 2016. The Bovespa Index (Ibovespa) or BVSP stock index in Brazil increased more than 60% after the economic crisis, though it was not performing well before and during the economic crisis.

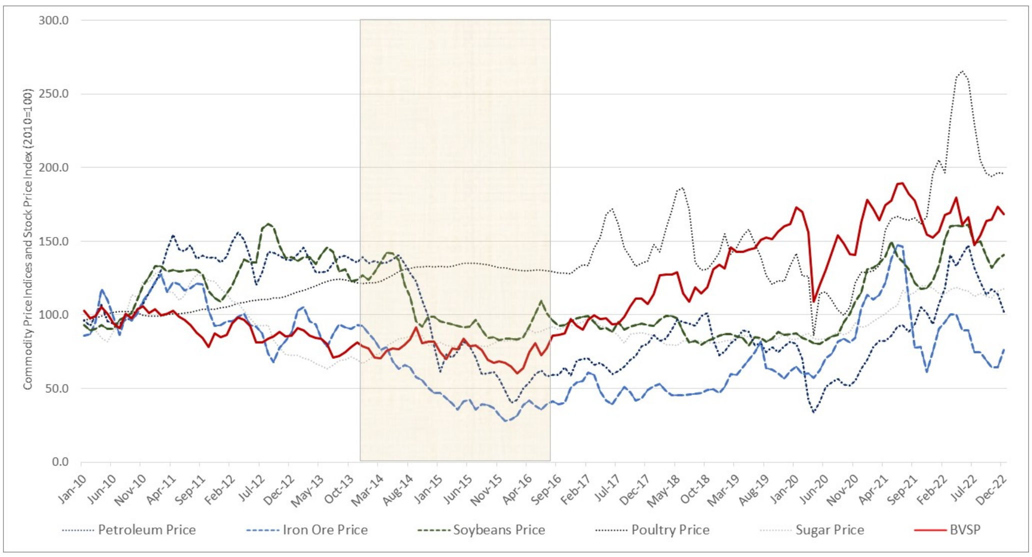

Figure 2. Trends in the Brazilian BVSP stock index and prices of petroleum, iron ore, soybeans, poultry, and sugar.

The relationship between the return of stocks and the percentage change in price of petroleum, price of iron ore, price of soybeans, price of poultry, and price of sugar are presented in Figures 3–7. The return on stocks is measured as the percentage change in the Brazilian BVSP stock index from one month to the next, and it is shown on the axis on the right-hand side of each figure.

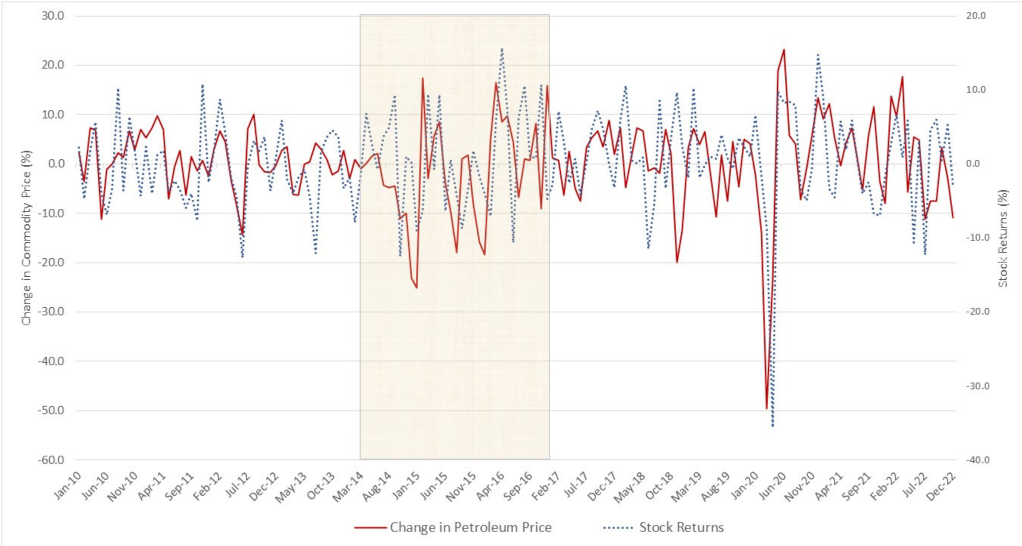

Figure 3. Relationship between Brazilian stock returns and the change in the price of petroleum. Note: The correlation coefficients between the change in petroleum price and stock returns in different time periods are as follows: 2010M1-2022M12 = 0.33; 2010M1-2014M3 = 0.45; 2014M4-2016M12 = 0.19; and 2017M1-2022M12 = 0.38.

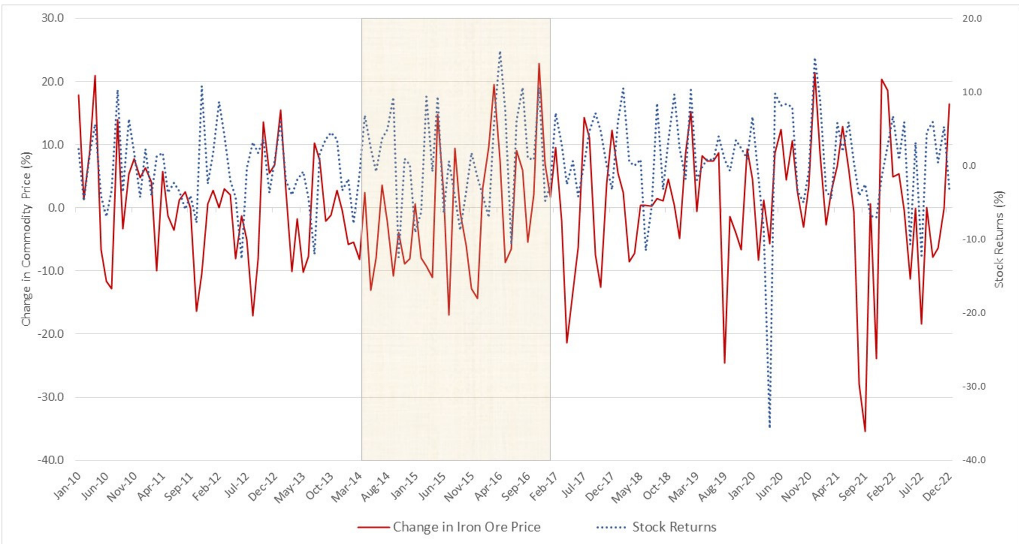

Figure 4. Relationship between Brazilian stock returns and the change in the price of iron ore. Note: The correlation coefficients between the change in iron ore price and stock returns in different time periods are as follows: 2010M1-2022M12 = 0.31; 2010M1-2014M3 = 0.31; 2014M4-2016M12 = 0.23; and 2017M1-2022M12 = 0.35.

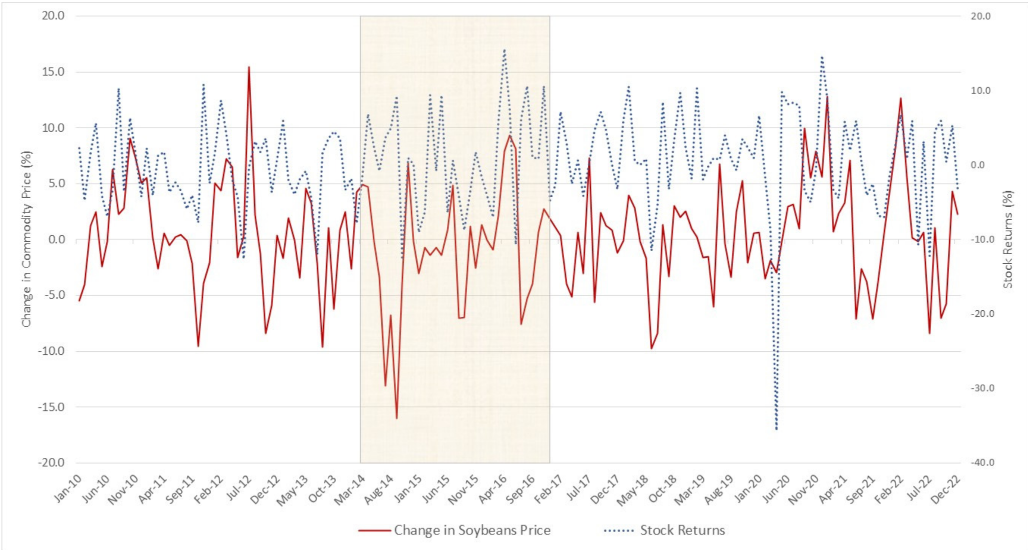

Figure 5. Relationship between Brazilian stock returns and the change in the price of soybeans. Note: The correlation coefficients between the change in soybean price and stock returns in different time periods are as follows: 2010M1-2022M12 = 0.18; 2010M1-2014M3 = 0.11; 2014M4-2016M12 = 0.01; and 2017M1-2022M12 = 0.31.

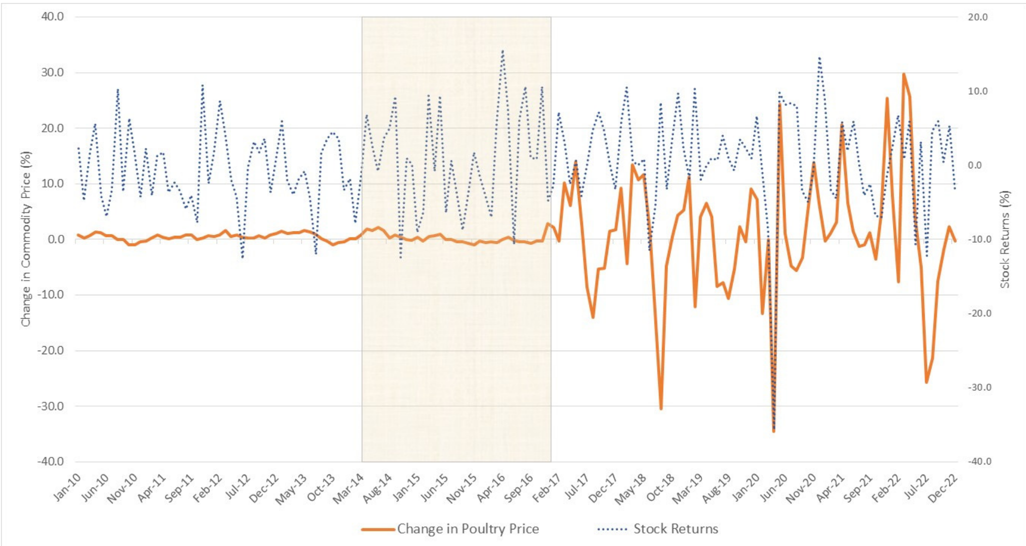

Figure 6. Relationship between Brazilian stock returns and the change in the price of poultry. Note: The correlation coefficients between the change in poultry price and stock returns in different time periods are as follows: 2010M1-2022M12 = 0.18; 2010M1-2014M3 = −0.16; 2014M4-2016M12 = 0.10; and 2017M1-2022M12 = 0.25.

This paper is organized as follows. Section 2 presents a review of the literature, Section 3 presents the methodology and data sources, Section 4 presents the empirical results and the discussion of the results, and Section 5 summarizes our conclusions.

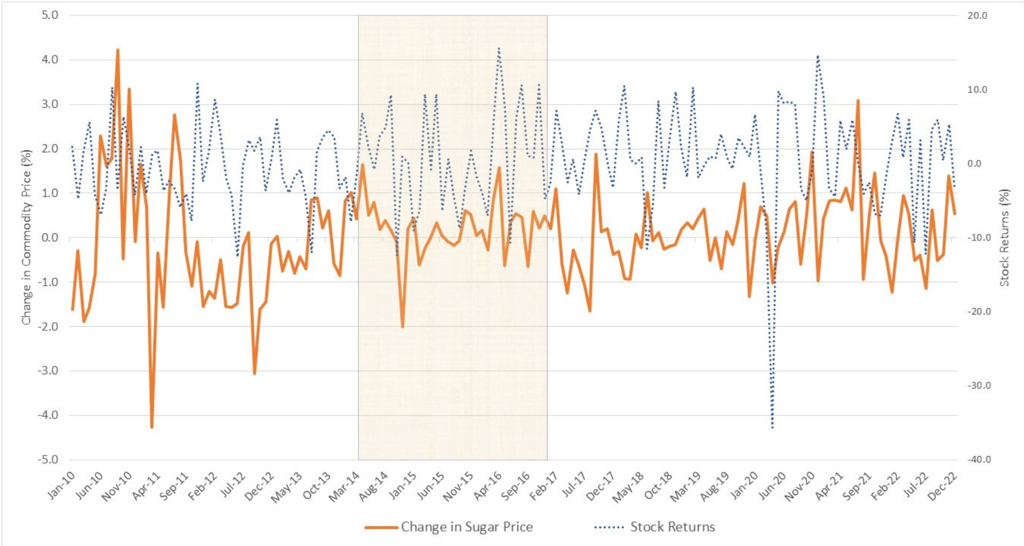

Figure 7. Relationship between Brazilian stock returns and the change in the price of sugar. Note: The correlation coefficients between the change in sugar price and stock returns in different time periods are as follows: 2010M1-2022M12 = 0.05; 2010M1-2014M3 = −0.10; 2014M4-2016M12 = 0.28; and 2017M1-2022M12 = 0.10.

2. Review of the Literature

A significant body of literature can be found on the nature of the association between commodity price shocks and stock returns. The empirical literature on the relationships between commodity prices and stock prices have produced mixed results. Some studies have found evidence for a negative relationship (see, for example, Tweneboah, Junior, and Kumah (2020) [4], Mensi, Hammoudeh, Shahzad, and Shahbaz (2017) [5], Sim and Shou (2015) [6], Xioa, Shou, Wen, and Wen (2018) [7], Mensi, Rehman, Hammoudeh, and Vo (2021) [8], Diaz, Molero, and de Garcia (2016) [9]), while others have found evidence for either a positive relationship (see, for example, Woode, Idun, and Kawar (2024) [10], Tweneboah, Junior, and Kumah (2020) [4], Mensi, Hammoudeh, Shahzad, and Shahbaz (2017) [5], Salisu and Oloko (2015) [11], Mensi, Rehman, Hammoudeh, and Vo (2021) [8], Manelli, Pace, and Leone (2024) [12], Watorek, Drozdz, Oswiecimka, and Stauszek (2019) [13]) or weak/no relationship (see, for example, Wei and Guo (2017) [14], Uddin, Hernandez, Shahzad, and Kang (2020) [15], Bastianin, Conti, and Manera (2016) [16], Babar, Ahmad, and Yousaf (2023) [17], Wadud, Gronwald, Durand, and Lee (2023) [18]). These inconsistent results can be ascribed to the use of different commodities, different data sets, and different estimation techniques or methodologies for such analyses. In this section, a summary of a wide variety of related studies is presented.

Manner, Rodriguez, and Stockler (2024) [19] conducted a study to analyze the vulnerabilities of stock markets that commodity-exporting countries face in terms of fluctuations in commodity prices and exchange rates and how these risks change over time. The study used daily data from 16 March 2001 to 12 March 2021 for five Latin American countries, namely, Argentina, Brazil, Chile, Mexico, and Peru, using the changepoint methods and non-parametric structural break tests for volatility and dependence. The study finds evidence of changes in risk and spillovers over time and increased spillover risk after the outbreak of the global financial crisis in 2008, as well as higher conditional risk following the COVID-19 outbreak.

A study by Woode, Idun, and Kawar (2024) [10] analyzed the co-movement between five agricultural commodities, namely, cocoa, coffee, corn, cotton, and soybeans, and five sub-Saharan African equities (BRVM, Ghana, Kenya, Mauritius, and Uganda) using monthly data from January 2017 and December 2022. The study used bivariate and multivariate wavelet analysis and found that commodities are the main driving force behind equities, with a few exceptions.

Using wavelets and quantile regression techniques, Tweneboah, Junior, and Kumah (2020) [4] investigated the asymmetric linkages between returns of spot gold prices and African stock markets. The study used daily data and found evidence that the relationship between gold and African stocks is frequency dependent and asymmetric in nature across the various timescales and quantiles, with a mixture of negative and positive connections across the various quantiles in the short and medium terms. The study also found that the returns of spot gold prices have a positive effect on stock markets in Ghana, Mauritius, and Nigeria, while they have a negative effect in Egypt, Morocco, South Africa, and Tunisia in the long term.

Wei and Guo (2017) [14] investigated the effects of oil price shocks on China's stock market using monthly data from February 1996 to October 2015. The study utilized three different types of oil price shocks, namely, oil supply shocks, aggregate demand shocks, and oil-specific demand shocks. Due to the presence of a structural break in December 2006, the sample period was divided into two sub-periods: 1996M2−2006M12 and 2007M1−2015M10. The findings of the study showed that the responses of stock volatility to oil shocks are almost negligible, though the responses are different in two sub-periods and crucially related to the causes of oil price changes. However, the responses of stock volatility to oil shocks were almost negligible. The study also found that speculative demand was the main cause of recent oil price fluctuations.

Using 5 min daily data from 11 April 2006 to 29 April 2019, Bouri, Lei, Zhang, Jalkh, and Xu (2021) [20] examined the dynamics of spillover effects on realized estimators of return distributions across US stocks, crude oil, and gold markets. The study used the time-varying parameter vector autoregression (TVP-VAR) model and found that all spillovers seem to intensify during crisis periods. Gold is a net receiver of all realized higher moments and jumps. The findings also suggest that stock and oil markets are net transmitters, while the gold market is a net receiver.

Using a multivariate and dynamic copula model, a study by Kielmann, Manner, and Min (2022) [21] investigated the dynamic, nonlinear dependence and risk spillover effects between BRICS stock returns and the different types of oil price shocks. The study used monthly data from February 1994 to April 2020 and measured the risk using the conditional value at risk (CoVaR), conditioning on one or more simultaneous oil and stock market shocks. The results of the study showed that during the early stages of the COVID-19 crisis, risk levels in stock markets in the BRICS increased, except for the Chinese market.

Mensi, Hammoudeh, Shahzad, and Shahbaz (2017) [5] investigated the relationship between crude oil prices and major regional stock markets under different investment horizons based on the daily closing spot prices for WTI crude oil. In addition, the study also analyzed the up and down short- and long-run risk spillovers between oil and stock markets by calculating three market risk measures. The study used a combination of the variational mode decomposition (VMD) method and static and time-varying symmetric and asymmetric copula functions. The results of the study showed that for the raw return series, there is a tail dependence between oil and all stock markets. The study also found evidence of upside and downside asymmetric short- and long-run risk spillovers from oil to stock markets and vice versa.

A study by Uddin, Hernandez, Shahzad, and Kang (2020) [15] examined the features of the risk spillover between the US stock market and oil and three precious metals. The study was conducted using daily data on the closing price series of the S&P 500 index and four major commodity futures, namely oil, gold, silver, and platinum. The study used two spillover measures, namely, a copula approach for tail dependence and conditional value at risk (CoVaR) spillover in their analysis. The results of the study found evidence for asymmetric tail dependence of the US stock market with silver and platinum, especially during market downturns. The study also found that gold and oil symmetrically co-moved with the US stock market under normal and extreme market scenarios. In addition, the

US stock market strongly influences oil and silver while gold weakly spillover to the US stock market.

Fasanya, Oyewole, and Adekoya (2021) [22] investigated the oil market–stock market nexus for the Gulf Cooperation Council countries. Using a weekly data set from 1992 to 2016, the study employed the symmetric ARDL and nonlinear ARDL estimation methods while accounting for structural breaks. The study found evidence for the large asymmetric response of most of the GCC stock markets to oil price shocks.

A study by Bastianin, Conti, and Manera (2016) [16] investigated the effects of crude oil price shocks due to oil supply and oil demand innovations on the stock market volatility of the G7 countries using impulse response functions. The study used monthly data over the period from February 1973 to January 2015. The results of the study found that oil supply shocks do not cause stock market volatility but demand shocks cause significant volatility in the G7 stock markets.

Employing monthly data from January 1973 to December 2007, Sim and Shou (2015) [6] examined the relationship between oil prices and US equities. To uncover two nuance features in the oil price–stock returns nexus, the study used the quantile-on-quantile approach to construct estimates of the effect that the quantiles of oil price shocks have on the quantiles of the US stock return. The study found that large, negative oil price shocks can affect US equities positively when the US market is performing well. The study also found evidence for an asymmetric relationship between oil prices on US equities.

A study by Salisu and Oloko (2015) [11] investigated the oil price-US stock nexus using daily data on the Brent and West Texas Intermediate crude oil price and the S&P 500 stock index for the period from 1 February 2002 to 4 April 2014. The study found evidence of a significant positive return spillover from the US stock market to the oil market. In addition, it also found evidence for bi-directional shock spillovers between the two markets.

Using the vector autoregression analysis and daily data from September 2005 to February 2010, Fayyad and Daly (2011) [23] investigated the relationship between oil price and stock market returns for five GCC countries, namely, Kuwait, Oman, UAE, Bahrain, Qatar, and two advanced economies (UK and USA). The study found that the impact of oil prices on stock returns increased after a rise in oil prices. It also found that some countries in the sample, namely, Qatar, UAE, and the UK, responded more to oil price shocks than others.

A study by Xioa, Shou, Wen, and Wen (2018) [7] investigated the impacts of oil price uncertainty on the aggregate and sectoral stock returns in China. Using the daily data covering the period from 10 May 2007 to 20 September 2017 and applying quantile regression, the study found evidence of significantly negative effects on the aggregate and sectoral stock returns in the bearish market.

Maghyereh, Awartani, and Bouri (2016) [24] investigated the relationship between oil and equities in eleven major stock exchanges around the globe from 2008 to 2015 using quarterly data. The study found evidence for the connectedness between the oil market and equity market across the sample countries. Though the study found evidence for the bi-directional information spillovers between the two markets, this relationship is largely dominated by the transmissions from the oil market to equity markets.

A study by Mensi, Rehman, Hammoudeh, and Vo (2021) [8] examined the dependence structure and systemic risk between two crude oil futures, one natural gas future, and stock markets in eight countries in the MENA region, namely, Egypt, Jordan, Kuwait, Qatar, Saudi Arabia, Tunisia, Turkey, and the UAE. The study used daily data covering the periods before and after the mid-2014 oil price crash and applied different techniques and measurements, including copula functions, the variational mode decomposition technique, and the conditional value at risk (CoVaR) measure. The study found evidence of a negative and positive average dependence between energy and stock markets before and after the oil crash in the short term. The results also found that the stock markets of the oil-exporting MENA countries are more affected by the energy price shocks than the oil-importing MENA countries.

Al-Yahyaee, Mensi, Sensoy, and Kang (2019) [25] analyzed dynamic return and risk spillovers between commodity futures of energy and precious metals and stock markets in the Gulf Cooperation Council countries. The study used daily data and applied dynamic equicorrelation models and a spillover index. The study found evidence of significant return and risk spillovers between the commodities and the GCC stock markets, specifically during the 2008–2009 global financial crisis. The study also found that silver, platinum, and energy futures markets were net transmitters of returns to stock markets, while precious metals and WTI oil were net transmitters of risk to GCC stock markets.

Using monthly data for the period from 1970 to 2014, Diaz, Molero, and de Garcia (2016) [9] analyzed the relationship between oil price volatility and stock returns in the G7 economies. The study estimated a vector autoregressive model while considering the structural breaks. The study found evidence of a negative reaction of stock markets in the G7 countries to an increase in oil price volatility. It also found evidence to conclude that volatility in world oil prices was more significant for stock markets than volatility in national oil prices.

A study by Salisu and Isah (2017) [26] examined the relationship between oil prices and stock prices in oil-exporting and oil-importing countries using monthly data covering the period from January 2000 to December 2015 and including eight net oil importing countries (Argentina, Australia, France, Germany, Japan, the Republic of Korea, the UK, and the USA) and five net oil-exporting countries (Kuwait, Indonesia, Nigeria, Qatar, and Saudi Arabia). The study used a nonlinear Panel ARDL model in their analysis. The results of the study found evidence to conclude that stock prices of both oil-exporting and oil-importing groups respond asymmetrically to changes in oil prices. However, the response was found to be stronger in the oil-importing countries.

Babar, Ahmad, and Yousaf (2023) [17] investigated the return and volatility spillover among agricultural commodities and emerging stock markets during various crises. The study used Diebold and Yilmaz's (2012) [27] approach to estimate the returns and volatility spillover. The results of the study revealed a weak relationship between agricultural commodities and emerging stock markets.

A study by Wadud, Gronwald, Durand, and Lee (2023) [18] studied the interdependence between the returns of specific energy and non-energy commodities and equities using two methods, namely, thick pen measure of association and multi-thickness thick pen measure of association. The study investigated 22 commodity futures from index and off-index commodities using daily data from 5 January 1993 to 24 December 2019. The study found evidence for a weak co-movement between equity and specific commodity futures.

Creti, Joets, and Mignon (2013) [28] studied the ties between price returns for 25 commodities, mainly covering energy raw materials and stocks, using a daily spot price series covering the period from 3 January 2001 to 28 November 2011. The study found that the correlations between commodity and stock markets evolve through time and are highly volatile, mainly after the 2007–2008 financial crisis.

A study by Manelli, Pace, and Leone (2024) [12] investigated the existence of a link between the performance of the Eurostoxx 50 index and the price of wheat futures and TTF natural gas using daily data covering the period from 25 February 2019 to 28 September 2023. The study found evidence of a positive and direct relationship between the three variables. The study also found that wheat futures prices show a greater effect on the stock market index than TTF gas futures prices. In addition, the study found evidence to support the claim that the Eurostoxx 50 index impacts the price trend of the two commodities.

A paper by Nagayev, Disli, Inghelbrecht, and Ng (2016) [29] investigated the relationship between commodities and equity index investments using daily spot prices for 17 commodities derived from the Dow Jones Commodity Index over the period from 20 January 1999 to 10 April 2015. The study used MGARCH-DCC and Wavelet Coherence analyses and found that correlations between commodity markets and the Dow Jones Islamic Market World Index are time varying and highly volatile during the study period.

Bagchi and Paul (2023) [30] investigated the effects of oil price shock on the stock price returns and currency exchange rates of G7 countries using daily data from 2 January 2017 to 29 June 2022 in the setting of the Russia–Ukraine conflict. The study used the fractionally integrated GARCH model to capture the effect of the crude oil price shock and found notable long-memory effects running from Brent crude oil price to all the stock price returns for all G7 countries.

A study by Mensi, Beljid, Boubaker, and Managi (2013) [31] investigated the return links and volatility transmission between the S&P 500 and price indices for four commodities, namely, energy, food, gold, and beverages. The study used daily data covering the period from 3 January 2000 to 31 December 2011 and employed a VAR-GARCH model. It found evidence for the highest conditional correlations between the S&P 500 and gold index and the S&P 500 and WTI index.

Adekoya, Asl, Oliyide, and Izadi (2023) [32] conducted a study to investigate the multifractality and cross-correlation between oil prices and prominent European and non-European stock markets before and during the recent Russia–Ukraine war. The study used multiscale multifractal analysis (MMA) and found a strong multifractal behavior in the oil and stock markets, while the war had a stronger direct influence on the persistence of the oil and the European stock markets.

A study by Escribano, Koczar, Jareno, and Esparcia (2023) [33] examined the connectedness between crude oil prices and several financial stock markets, namely, China (SSE Composite), Germany (DAX), Mexico (MEXBOL), Norway (OSEAX), Poland (WIG), Russia (RTS), Spain (IBEX), the United Kingdom (FTSE), and the United States (S&P). The study used daily data from 4 January 2000 to 27 February 2023 and applied a Dynamic Conditional Correlation Skew Student Copula model and the connectedness index by Diebold and Yilmaz (2012) [27]. The findings of the study showed that importing countries showed a negative pairwise dependence on BRENT more frequently than exporting countries. In addition, the study also found that connectedness in terms of the returns and volatility among crude oil prices and stock markets has affected the interdependencies between them.

3. Methodology and Data

3.1. Estimation Methodology

In this paper, we contribute to the emerging empirical literature dealing with the link between commodity price shocks and stock market returns in Brazil. The objective of this study is to examine the relationship between commodity price shocks and stock returns in Brazil, focusing on five primary commodities, namely, petroleum, iron ore, soybeans, poultry, and sugar, using monthly data from January 2010 to December 2022.

In order to formally investigate the relationship between the commodity price shocks and stock returns, we utilize a structural vector autoregressive model (SVAR) with the following variables: stock returns, change in petroleum price, change in iron ore price, change in soybean price, change in poultry price, change in sugar price, economic activity, and inflation rate. The SVAR models have widely been used in the field of commodity and energy markets and, according to Chen, Lioa, Tang, and Wei (2016) [34], the SVAR model has advantages in analyzing dynamic relationships among relevant time sequence variables. The formal investigation is based on the following SVAR model:

$$A_0 x_t = \alpha + \sum_{k=1}^{2} A_k x_{t-k} + \vartheta_t \quad (1)$$

where $x_t = (\Delta sr_t, \Delta pep_t, \Delta iop_t, \Delta sbp_t, \Delta pop_t, \Delta sup_t, \Delta ipi_t, \Delta cpi_t, \Delta exr_t)'$ is a vector of nine variables, Δsr_t is the stock returns measured as the percentage change in the monthly BVSP stock index in Brazil, Δpep_t is the percentage change in monthly petroleum price (US Dollars per barrel), Δiop_t is the percentage change in monthly iron ore price, Δsbp_t is the percentage change in monthly soybean price, Δpop_t is the percentage change in monthly poultry price, Δsup_t is the percentage change in monthly sugar price, and Δipi_t is the percentage change in the monthly industrial production index (2010 = 100), where Δcpi_t is the Brazilian inflation rate measured as the percentage change in the monthly consumer price index (2010 = 100), Δexr_t is the percentage change in the monthly nominal exchange rate (Brazilian Real per US Dollar), α, A_0, and A_k are unknown coefficients and vectors to be estimated, and ϑ_t is the vector of serially and mutually uncorrelated structural innovations.

Assuming that A_0 is reversible, for estimation purposes, the SVAR model is expressed in the reduced form as follows:

$$x_t = b + \sum_{k=1}^{2} B_k x_{t-k} + \in_t \tag{2}$$

where $b = A_o^{-1}a$, $B_k = A_0^{-1}A_k$ for all k, and $\in_t = A_0^{-1}\vartheta_t$ is the vector of estimated residuals in the reduced form. The number of lags (of k = 2) has been determined by the final prediction error, Akaike information criterion, and Hannan–Quinn information criterion.

In addition to the SVAR model, we also specify a multiple regression model to analyze the effects of commodity prices on stock returns. The second model is specified as follows:

$$\begin{aligned} lnBVSP_t \quad &= \beta_0 + \beta_1 lnPEP_t + \beta_2 lnIOP_t + \beta_3 lnSBP_t + \beta_4 lnPOP_t + \beta_5 lnSUP_t + \beta_6 lnIPI_t \\ &\quad + \beta_7 lnCPI_t + \beta_8 lnEXR_t + \beta_9 lnS\&P_t + \varepsilon_t \end{aligned} \tag{3}$$

where $lnBVSP_t$ is the log of the Brazilian BVSP stock index, $lnPEP_t$ is the log of petroleum price (.S Dollars per barrel), $lnIOP_t$ is the log of iron ore price, $lnSBP_t$ is the log of soybean price, $lnPOP_t$ is the log of poultry price, $lnSUP_t$ is the log of sugar price, $lnIPI_t$ is the log of the industrial production index (2010 = 100), $lnCPI_t$ is the log of the Brazilian consumer price index (2010 = 100), $lnEXR_t$ is the log of the nominal exchange rate (Brazilian Real per US Dollar), $lnS\&P_t$ is the log of the S&P500 stock index in the United States, and ε_t is an error term.

Before estimating both the SVAR model and the multiple regression model, unit root properties of the variables were checked using the ADF test and the Phillips–Perron test since the SVAR model requires at least one of the variables included in the model to be nonstationary. In addition, the Johansen cointegration test was also conducted to test whether the variables included in the regression model are cointegrated.

3.2. Data and Data Sources

The stock returns are measured as the percentage change in the monthly Bovespa Index (Ibovespa) in Brazil. The data on the Bovespa Index and S&P 500 index were obtained from Yahoo Finance (2024), https://finance.yahoo.com/quote/%5EBVSP/history/ (accessed on 30 August 2024) [35]. The percentage changes in global oil prices, Δpep_t, are calculated as the month-to-month logarithmic changes in the Brent crude oil price. The monthly data on iron ore price, soybean price, poultry price, and sugar price were obtained from the International Monetary Fund (2024) *Primary Commodity Price System* (https://data.imf.org/?sk=471dddf8-d8a7-499a-81ba-5b332c01f8b9) (accessed on 30 August 2024) [36]. The level of economic activity was measured using the monthly industrial production index (2010 = 100), and the data on the industrial production index were obtained from the International Monetary Fund (2024) International Financial Statistics Yearbook 2024 [37]. The Brazilian inflation rate was measured as the percentage change in the monthly consumer price index (2010 = 100) and, the CPI was obtained from the International Monetary Fund International Financial Statistics Yearbook 2024 [37]. The data on the monthly nominal exchange rate (Brazilian Real per US Dollar) was obtained from the International Monetary Fund International Financial Statistics Yearbook 2024 [37].

4. Empirical Results and Discussions

4.1. Results of the SVAR Model

In this section, we discuss the results of the SVAR model, focusing on the relative contributions of these eight types of structural innovations to stock return changes using impulse response functions and variance decomposition analysis. Though our study uses data covering the period from January 2010 to December 2022, to account for the Brazilian economic crisis between 2014 and 2016, we have also analyzed the effects of commodity prices on stock prices in three different time periods, namely, before the economic crisis (January 2010–March 2014), during the economic crisis (April 2014–December 2016), and after the economic crisis (January 2017–December 2022). The extent of the fluctuations of the stock returns explained by innovations from each shock can be identified using a generalized forecast error variance decomposition analysis. Table 2 presents the summary of contributions of various chocks to stock returns in Brazil during the 2010–2022 period. The accompanying impulse response function is presented in Figure 8.

Table 2. Contributions of various shocks to stock return fluctuations (%). Sample period: 2010M01–2022M12.

Month	S.E.	SR	PEP	IOP	SBP	POP	SUP	CPI	EXR	IPI
1	0.045	100.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00
2	0.078	66.08	13.82	0.65	0.01	0.17	0.06	2.24	16.93	0.03
3	0.099	58.23	18.98	2.31	0.11	0.52	0.06	4.24	15.55	0.02
4	0.114	53.76	20.19	3.95	0.21	0.93	0.05	6.07	14.84	0.01
5	0.124	51.65	19.67	5.18	0.27	1.44	0.07	7.53	14.18	0.02
6	0.132	50.49	18.65	5.99	0.30	2.01	0.14	8.63	13.76	0.03
7	0.137	49.76	17.61	6.49	0.32	2.64	0.26	9.46	13.42	0.04
8	0.142	49.21	16.67	6.79	0.37	3.29	0.42	10.09	13.11	0.06
9	0.146	48.73	15.85	6.97	0.47	3.93	0.62	10.57	12.80	0.06
10	0.150	48.29	15.13	7.07	0.63	4.52	0.85	10.95	12.49	0.06
11	0.153	47.86	14.52	7.12	0.86	5.03	1.11	11.26	12.19	0.06

Note: This table shows the variance decomposition of SR using Cholesky (d.f. adjusted) factors for Cholesky one standard deviation (d.f. adjusted) innovations. Cholesky ordering: SR, PEP, IOP, SBP, POP, SUP, CPI, EXR, IPI, where SE is the standard error, SR is the stock returns, PEP is the percentage change in petroleum price, IOP is the percentage change in iron ore price, SBP is the percentage change in soybean price, POP is the percentage change in poultry price, SUP is the percentage change in sugar price, CPI is the percentage change in the consumer price index (inflation rate), EXR is the percentage change in the nominal exchange rate, and IPI is the percentage change in the industrial production index.

Based on the variance decomposition analysis results presented in Table 2, stock return is mostly driven by the exchange rate (following its own shock). Of the commodity prices, petroleum is the most important commodity (accounting for 20.2% of the fluctuations of stock returns in Month 4), followed by iron ore (accounting for 4.0% of the fluctuations of stock returns in Month 4), which affects the stock return. The other three commodities, soybeans, poultry, and sugar, have minor effects on stock returns. Table 2 also shows that the effects of these shocks last only about six to seven months. This is also evident from the impulse response functions presented in Figure 8. According to Figure 8, shocks in all commodity prices have positive effects on stock returns in the first three to four months, while the inflation rate, the exchange rate, and production shocks have negative effects on stock returns in the first three months.

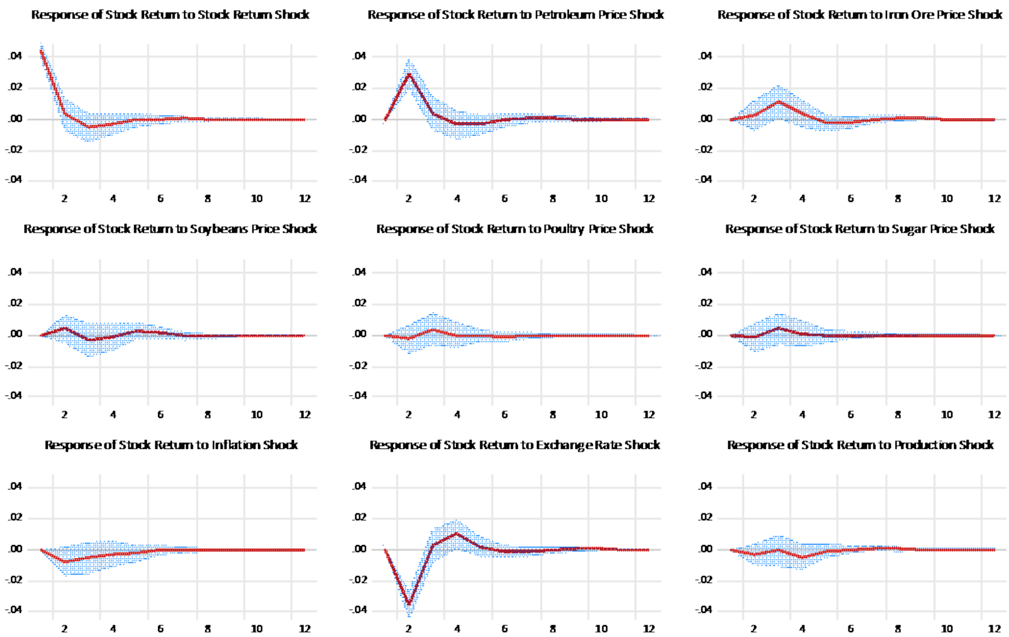

Figure 8. Impulse response functions. Sample period: 2010M01–2022M12. Note: This is a response to Cholesky one SD (d.f. adjusted) innovations. A 95% C.I. using analytic asymptotic standard errors.

Table 3 presents the summary of the contributions of various shocks to stock returns in Brazil during the 2010–2014 period, which is the period before the economic crisis. The accompanying impulse response function is presented in Figure 9. Similar to the variance decomposition analysis results presented in Table 2, in this time period, stock return is also mostly driven by the exchange rate (following its own shock). However, during this period, the contribution of petroleum dropped significantly, accounting for only 3.57% in Month 4. Soybeans also made a similar contribution. Unlike during the period from 2010 to 2022, during the pre-economic crisis period, all five export commodities made a much higher contribution to the variability of stock returns, lasting about nine months. The impulse response functions presented in Figure 9 reveal that shocks in petroleum prices have a positive effect, while the other four commodities have negative effects on stock returns in the first two to three months.

The summary of contributions of various shocks to stock returns in Brazil during the economic crisis period of 2014–2016 is presented in Table 4. The accompanying impulse response function is presented in Figure 10. Though during this period stock returns are mostly driven by the exchange rate (following its own shock), four of the five commodities also explained a larger percentage of the variation in stock returns, jointly accounting for about 20% of the variation in Month 3. Compared to the two time periods discussed earlier, during the economic crisis period, all five export commodities have made a much larger contribution to the variability of stock returns, with effects lasting about ten months. The impulse response functions presented in Figure 10 reveal that shocks in petroleum prices and iron ore prices have a positive effect on stock returns in the first four to six months.

Table 5 presents the summary of the contributions of various shocks to stock returns in Brazil during the 2017–2022 period, which is the period after the economic crisis in Brazil. The accompanying impulse response function is presented in Figure 11. Similar to the period covered by the economic crisis, during the post-economic crisis period, stock returns are mostly driven by the exchange rate (following its own shock). However, four of the five commodities also showed a larger percentage of the variation in stock returns, jointly accounting for about 35% of the variation in Month 4. As was the case during the economic crisis period, all five export commodities have made a much larger contribution to the variability of stock returns, with effects lasting about seven months. The impulse response functions presented in Figure 11 reveal that shocks in the petroleum price, iron ore price, soybean price, and poultry price have a positive effect on stock returns in the first three to four months.

Table 3. Contributions of various shocks to stock return fluctuations (%). Sample period: 2010M01–2014M03.

Month	S.E.	SR	PEP	IOP	SBP	POP	SUP	CPI	EXR	IPI
1	0.035	100.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00
2	0.060	69.71	2.69	0.57	0.73	1.74	0.02	0.43	24.12	0.00
3	0.066	68.89	3.58	0.82	0.67	1.44	1.37	0.36	22.53	0.33
4	0.067	68.24	3.57	0.81	0.70	1.48	2.18	0.39	21.97	0.66
5	0.069	66.21	4.81	0.80	0.75	1.43	3.12	0.57	21.54	0.77
6	0.070	64.26	5.95	0.77	0.71	1.37	3.68	0.98	21.52	0.76
7	0.071	63.63	6.05	0.80	0.71	1.34	3.84	1.46	21.42	0.75
8	0.071	63.05	6.19	0.81	0.80	1.42	3.85	1.95	21.20	0.74
9	0.072	61.74	7.07	0.81	0.92	1.72	3.77	2.43	20.80	0.75
10	0.073	60.20	8.00	0.92	1.00	2.16	3.68	2.84	20.38	0.82
11	0.074	59.05	8.46	1.09	1.05	2.50	3.66	3.15	20.11	0.92
12	0.074	58.36	8.60	1.21	1.08	2.64	3.78	3.32	20.01	0.99

Note: This table shows the variance decomposition of SR using Cholesky (d.f. adjusted) factors for Cholesky one standard deviation (d.f. adjusted) innovations. Cholesky ordering: SR, PEP, IOP, SBP, POP, SUP, CPI, EXR, IPI, where SE is the standard error, SR is the stock returns, PEP is the percentage change in petroleum price, IOP is the percentage change in iron ore price, SBP is the percentage change in soybean price, POP is the percentage change in poultry price, SUP is the percentage change in sugar price, CPI is the percentage change in the consumer price index (inflation rate), EXR is the percentage change in the nominal exchange rate, and IPI is the percentage change in the industrial production index.

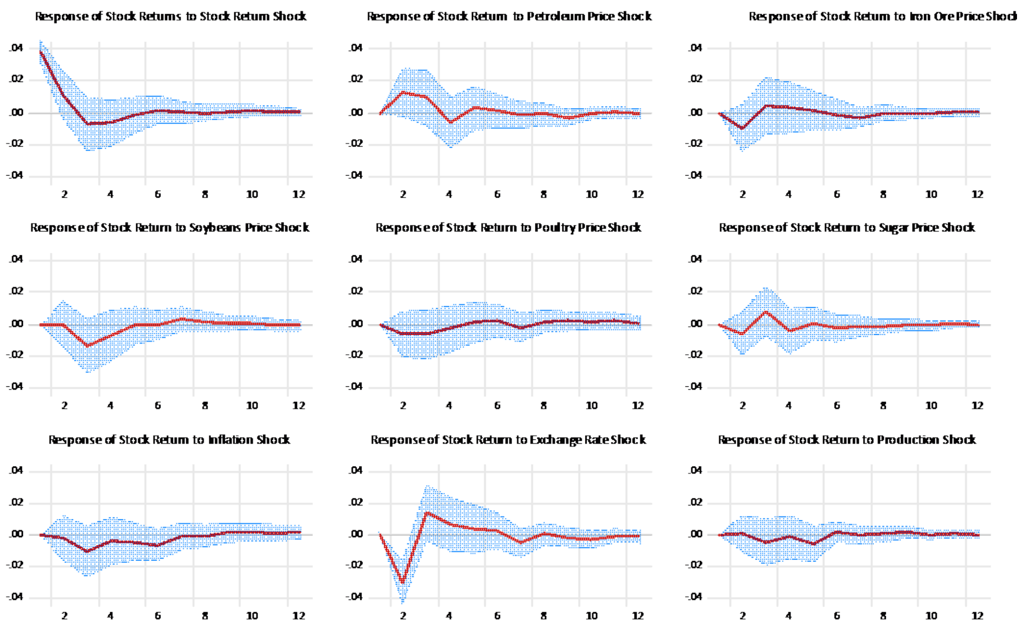

Figure 9. Impulse response functions. Sample period: 2010M01–2014M03. Note: This is a response to Cholesky one SD (d.f. adjusted) innovations. A 95% C.I. using analytic asymptotic standard errors.

Table 4. Contributions of various shocks to stock return fluctuations (%). Sample period: 2014M04–2016M12.

Month	S.E.	SR	PEP	IOP	SBP	POP	SUP	CPI	EXR	IPI
1	0.046	100.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00
2	0.063	58.32	1.90	5.48	1.79	4.14	4.54	2.10	21.58	0.15
3	0.092	33.35	4.64	7.90	1.48	2.16	2.56	1.65	44.29	1.98
4	0.100	38.59	3.87	7.37	1.37	1.80	5.82	1.80	37.56	1.83
5	0.106	36.05	6.52	6.69	1.56	1.64	8.10	1.99	34.54	2.92
6	0.112	32.85	7.40	6.07	1.48	1.49	8.42	1.99	37.54	2.76
7	0.116	31.22	7.24	5.66	1.49	1.73	10.70	2.30	37.09	2.57
8	0.121	29.28	7.90	5.31	2.29	3.59	12.59	2.39	34.22	2.44
9	0.128	29.27	9.12	4.76	3.06	6.62	12.16	2.14	30.68	2.19
10	0.136	33.85	8.97	4.42	3.10	7.69	11.04	1.89	27.00	2.05
11	0.142	37.72	8.49	4.29	2.83	7.37	10.35	2.04	24.96	1.94
12	0.147	38.07	8.18	4.03	2.84	6.91	9.75	2.39	25.98	1.84

Note: This table shows the variance decomposition of SR using Cholesky (d.f. adjusted) factors for Cholesky one standard deviation (d.f. adjusted) innovations. Cholesky ordering: SR, PEP, IOP, SBP, POP, SUP, CPI, EXR, IPI, where SE is the standard error, SR is the stock returns, PEP is the percentage change in petroleum price, IOP is the percentage change in iron ore price, SBP is the percentage change in soybean price, POP is the percentage change in poultry price, SUP is the percentage change in sugar price, CPI is the percentage change in the consumer price index (inflation rate), EXR is the percentage change in the nominal exchange rate, and IPI is the percentage change in the industrial production index.

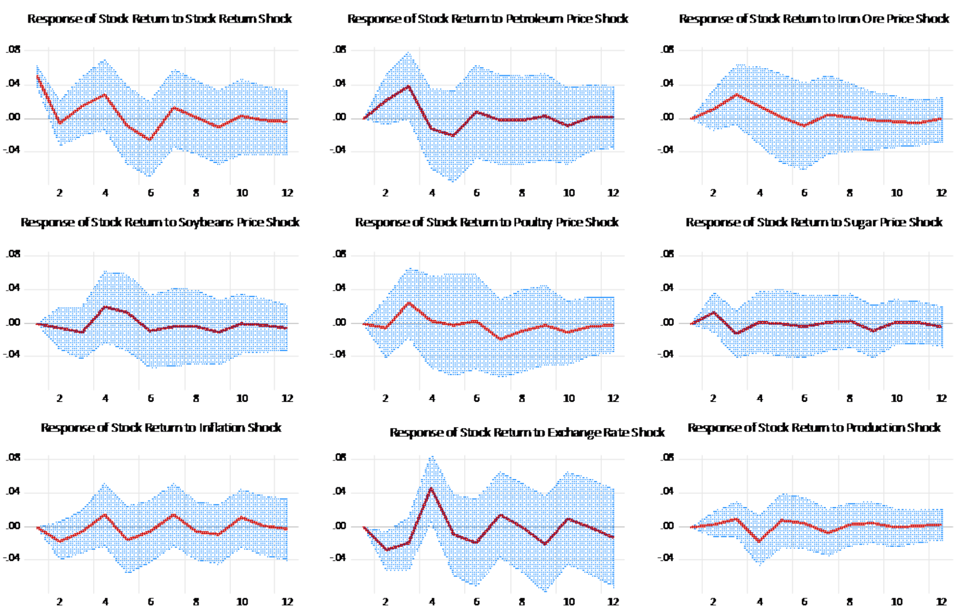

Figure 10. Impulse response functions. Sample period: 2014M04–2016M12. Note: This is a response to Cholesky one SD (d.f. adjusted) innovations. 95% C.I. using analytic asymptotic standard errors.

Based on the results discussed in this section, we can find evidence to conclude that stock returns in Brazil respond significantly to commodity price volatility. This response is more prominent during the 2014–2016 economic crisis in Brazil.

Table 5. Contributions of various shocks to stock return fluctuations (%). Sample period: 2017M01–2022M12.

Month	S.E.	SR	PEP	IOP	SBP	POP	SUP	CPI	EXR	IPI
1	0.043	100.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00
2	0.080	62.67	15.44	1.22	0.01	0.05	0.62	0.29	19.41	0.28
3	0.097	54.73	19.21	7.51	0.16	0.05	1.58	0.58	15.45	0.73
4	0.104	49.98	20.08	11.44	0.28	0.07	3.32	0.50	13.72	0.62
5	0.108	47.79	20.09	13.08	0.29	0.13	4.60	0.49	12.90	0.64
6	0.110	46.55	19.75	13.06	0.36	0.30	5.76	0.56	12.81	0.85
7	0.111	45.39	19.22	12.68	0.72	0.51	6.60	0.72	13.15	1.01
8	0.113	44.13	18.60	12.48	1.36	0.75	7.19	0.94	13.50	1.05
9	0.115	43.04	18.03	12.49	2.05	0.95	7.56	1.21	13.65	1.02
10	0.117	42.29	17.56	12.53	2.64	1.06	7.79	1.49	13.59	1.05
11	0.118	41.89	17.17	12.53	3.08	1.09	7.91	1.75	13.38	1.19
12	0.119	41.75	16.85	12.46	3.40	1.07	7.97	1.96	13.13	1.41

Note: This table shows the variance decomposition of SR using Cholesky (d.f. adjusted) factors for Cholesky one standard deviation (d.f. adjusted) innovations. Cholesky ordering: SR, PEP, IOP, SBP, POP, SUP, CPI, EXR, IPI, where SE is the standard error, SR is the stock returns, PEP is the percentage change in petroleum price, IOP is the percentage change in iron ore price, SBP is the percentage change in soybean price, POP is the percentage change in poultry price, SUP is the percentage change in sugar price, CPI is the percentage change in the consumer price index (inflation rate), EXR is the percentage change in the nominal exchange rate, and IPI is the percentage change in the industrial production index.

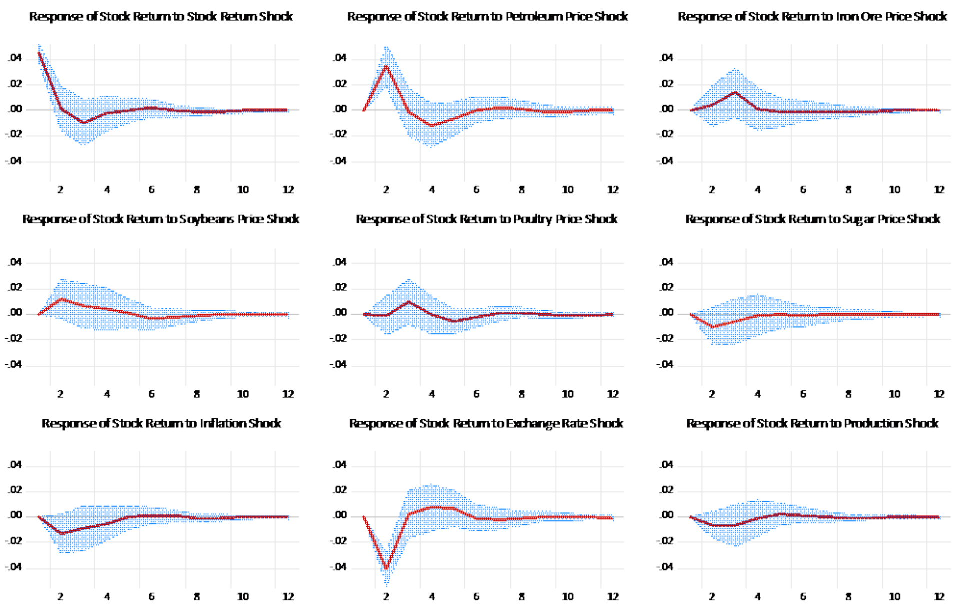

Figure 11. Impulse response functions. Sample period: 2017M01–2022M12. Note: This is a response to Cholesky one SD (d.f. adjusted) innovations. 95% C.I. using analytic asymptotic standard errors.

4.2. Stationarity and Cointegration Tests

Before estimating the multiple regression model specified in Equation (3), it is necessary to test the stationarity of the variables. To check the stationarity of the variables, we used two unit root tests, namely, the augmented Dickey–Fuller (ADF) test (Dickey and Fuller, 1979) [38] and the Phillips–Perron (PP) test (Phillips and Perron, 1988) [39]. The null hypothesis of these tests is the existence of a unit root. The results of the unit root tests are presented in Table 6. The results show that all variables, except the *POP* variable, are stationary at the first difference, while the *POP* variable is stationary at that level.

Table 6. Results of unit root tests.

Variable	ADF Test		PP Test	
	Level	**Difference**	**Level**	**Difference**
BVSP	−1.925 (0.639)	−14.774 *** (0.000)	−2.045 (0.574)	−14.692 *** (0.000)
PEP	−2.527 (0.315)	−12.259 *** (0.000)	−2.194 (0.491)	−11.971 *** (0.000)
IOP	−1.654 (0.769)	−13.711 *** (0.000)	−1.372 (0.867)	−13.460 *** (0.000)
SBP	−2.745 (0.219)	−11.417 *** (0.000)	−2.219 (0.476)	−11.081 *** (0.000)
POP	−3.447 ** (0.047)	−15.001 *** (0.000)	−3.689 ** (0.024)	−15.012 *** (0.000)
SUP	−2.571 (0.294)	−12.413 *** (0.000)	−2.513 (0.322)	−12.559 *** (0.000)
IPI	−1.714 (0.743)	−5.929 *** (0.000)	−1.928 (0.622)	−34.298 *** (0.000)
CPI	−2.641 (0.262)	−8.004 *** (0.000)	−2.231 (0.470)	−7.994 *** (0.000)
EXR	−1.333 (0.877)	−16.917 *** (0.000)	−1.488 (0.832)	−16.966 *** (0.000)
S&P	−2.479 (0.338)	−16.253 *** (0.000)	−2.507 (0.324)	−16.254 *** (0.000)

Note: BVSP is the log of the Brazilian BVSP stock index, PEP is the log of petroleum price, IOP is the log of iron ore price, SBP is the log of soybean price, POP is the log of poultry price, SUP is the log of sugar price, IPI is the log of the industrial production index (2010 = 100), CPI is the log of the Brazilian consumer price index, EXR is the log of the nominal exchange rate, S&P is the log of the S&P500 stock index. Figures in the parentheses are standard errors. A constant and a linear trend are included in all models. *** and ** represent the 1% and 5% levels of significance, respectively.

After testing for the presence of unit roots of each variable, the next step involves testing for cointegration among the variables included in the specified model. For this purpose, we have used the Johansen cointegration test (Johansen, 1988, 1991) [40,41]. The results of the Johansen cointegration test are presented in Table 7. The results presented in Table 7 reveal that the Trace test indicates the existence of two cointegrating equations at the 5% level of significance, while the Maximum Eigenvalues test also indicates the existence of one cointegrating equation at the 5% level of significance, implying that the ten variables included in Equation (3) are cointegrated.

Table 7. Results of the Johansen cointegration test.

Hypothesized	Trace Test		Maximum Eigenvalues Test	
No. of CE(s)	**Trace Statistic**	***p*-Value**	**Max. EV Statistic**	***p*-Value**
$r = 0$	288.12 ***	0.0000	87.87 ***	0.0001
$r \leq 1$	200.25 **	0.0358	46.08	0.4643
$r \leq 2$	154.17 *	0.0943	39.14	0.5490
$r \leq 3$	115.03	0.1841	35.92	0.4029
$r \leq 4$	79.11	0.3948	26.54	0.6650
$r \leq 5$	52.57	0.5244	22.75	0.5495
$r \leq 6$	29.81	0.7284	12.37	0.9168
$r \leq 7$	17.44	0.6073	10.97	0.6506
$r \leq 8$	6.48	0.6392	6.30	0.5746
$r \leq 9$	0.17	0.6781	0.17	0.6781

Note: This table presents the results of the Johansen cointegration tests. Figures in parentheses are MacKinnon–Haug–Michelis (1999) [42] *p*-values, and r is the hypothesized number of cointegrating equations. The asterisks ***, **, and * represent statistical significance at the 1%, 5%, and 10% levels, respectively.

4.3. Regression Analysis

After testing the stationarity of the variables and the presence of a cointegrating relationship among the variables included in the multiple regression model specified in Equation (3), the model was estimated using the Ordinary Least Squares (OLS) estimation method. To be consistent with the approach followed in estimating the SVAR model, the multiple regression model specified in Equation (3) was estimated for four periods: (a) the period from January 2010 to December 2022; (b) the period before the economic crisis (January 2010–March 2014); (c) the period during the economic crisis (April 2014–December 2016); and (d) the period after the economic crisis (January 2017–December 2022). The estimated results obtained using the OLS estimation method are presented in Table 8.

Table 8. Results of regression analysis. Dependent variable: $BVSP$.

Variable	Model 1	Model 2	Model 3	Model 4
$Constant$	5.1766 *** (0.000)	8.4913 *** (0.000)	5.7616 (0.221)	1.1079 (0.565)
PEP	0.1824 *** (0.001)	0.1537 (0.318)	0.1937 ** (0.012)	0.0692 (0.519)
IOP	0.5042 *** (0.000)	0.0228 (0.739)	0.2705 ** (0.013)	0.2666 *** (0.000)
SBP	−0.6532 *** (0.000)	0.1752 ** (0.020)	−0.2014 (0.144)	−0.2310 ** (0.025)
POP	−0.0888 (0.326)	0.3300 (0.642)	−0.3426 (0.683)	−0.1231 (0.302)
SUP	0.2504 *** (0.000)	−0.1525 ** (0.039)	0.1898 (0.543)	−0.7974 *** (0.000)
IPI	−0.0258 (0.844)	−0.3277 *** (0.003)	0.1560 (0.172)	−0.0429 (0.742)
CPI	0.9958 *** (0.001)	−2.8665 ** (0.010)	0.1959 (0.711)	1.6998 *** (0.000)
EXR	−0.0343 (0.758)	−0.3115 * (0.057)	0.1027 (0.474)	−0.3095 * (0.086)
$S\&P$	0.2107 *** (0.000)	0.3877 ** (0.028)	1.9831 *** (0.000)	0.6653 *** (0.000)
$Adjusted\ R^2$	0.8695	0.8569	0.8877	0.8694
$No.of\ Observations$	156	51	33	72

Note: Model 1 represents the period from 2010M01 to 2022M12; Model 2 represents the period from 2010M01 to 2014M03; Model 3 represents the period from 2014M04 to 2016M12; Model 4 represents the period from 2017M01 to 2022M12. BVSP is the log of the Brazilian BVSP stock index, PEP is the log of petroleum price, IOP is the log of iron ore price, SBP is the log of soybean price, POP is the log of poultry price, SUP is the log of sugar price, IPI is the log of industrial production index, CPI is the log of the Brazilian consumer price index, EXR is the log of the nominal exchange rate, S&P is the log of and S&P500 stock index. Figures in the parentheses are standard errors. The asterisks ***, **, and * represent statistical significance at the 1%, 5%, and 10% levels, respectively.

The results presented in Table 8 show that to some extent, the results of the regression analysis are consistent with the results of the SVAR model. In Model 1, which represents the entire study period of January 2010 to December 2022, prices of petroleum, iron ore, and sugar have a positive and statistically significant effect on the BVSP stock index. The price of soybeans has a negative and statistically significant effect, while the price of poultry has a negative but insignificant effect on the BVSP stock index. During the pre-economic crisis period, as shown in Model 2, prices of petroleum, iron ore, soybeans, and poultry have a positive effect, while the price of sugar has a negative effect on the BVSP stock index. During the economic crisis period, as shown in Model 3, prices of petroleum, iron ore, and sugar have a positive effect, while prices of soybeans and poultry have a negative effect on the BVSP stock index. During the post-economic crisis period, as shown in Model 4, prices of petroleum and iron ore have a positive effect, while prices of sugar, soybeans, and poultry have a negative effect on the BVSP stock index. Based on the results discussed in this section, we can find evidence to conclude that prices of petroleum and iron ore have a positive and significant effect, while the prices of sugar, soybeans, and poultry have mixed effects on the stock index. In addition, the S&P500 index shows a positive and statistically significant effect on the BVSP stock index in Brazil during all time periods.

5. Conclusions

In this paper, we contribute to the emerging empirical literature dealing with the relationship between commodity price shocks and stock market returns focusing on a leading commodity-exporting country. The objective of this study is to investigate the relationship between commodity price shocks and stock returns in Brazil, focusing on five primary commodities, namely, petroleum, iron ore, soybeans, poultry, and sugar. This study investigates the relationship between commodity price shocks and stock returns in Brazil using a structural vector autoregressive (SVAR) model and a multiple regression model. This study uses monthly data on prices of five major export commodities, stock prices, and several control variables, covering the period from January 2010 to December 2022. To account for the Brazilian economic crisis between 2014 and 2016, we have analyzed the effects of commodity prices on stock prices in three different time periods, namely, before the economic crisis (January 2010–March 2014), during the economic crisis (April 2014–December 2016), and after the economic crisis (January 2017–December 2022). The empirical results of the SVAR model provide evidence to conclude that stock returns increase following a positive global commodity price shock or a positive exchange rate shock. The effects are more noticeable during the economic crisis in Brazil. The results also show that the volatility of Brazilian stock returns is mostly explained by global oil prices and exchange rate movements in the long run.

Based on the variance decomposition analysis results for the sample period of 2010–2022, stock return is mostly driven by the exchange rate (following its own shock). Of the commodity prices, petroleum is the most important commodity that affects the stock return, followed by iron ore. The other three commodities, soybeans, poultry, and sugar, have minor effects on stock returns. The results also show that the effects of these shocks last only about six to seven months. The impulse response functions covering this period also show shocks in all commodity prices and have positive effects on stock returns in the first three to four months, while the inflation rate, the exchange rate, and production shocks have negative effects on stock returns in the first three months.

During the pre-economic crisis period of 2010–2014, stock returns were mostly driven by the exchange rate (following its own shock). However, during this period, the contribution of petroleum dropped significantly, while soybeans also made a similar contribution. Unlike during the period from 2010 to 2022, during the pre-economic crisis period, all five export commodities have made a much higher contribution to the variability of stock returns, lasting about nine months. The impulse response functions covering this period reveal that shocks in global petroleum prices have a positive effect, while the other four commodities have negative effects on stock returns in the first two to three months.

During the Brazilian economic crisis period of 2014–2016, though stock returns were mostly driven by the exchange rate (following its own shock), four of the five commodities also explained a larger percentage of the variation in stock returns, jointly accounting for about 20% of the variation in Month 3. Compared to the two time periods discussed earlier, during the economic crisis period, all five export commodities have made a much larger contribution to the variability of stock returns, with effects lasting about ten months. The impulse response functions for this period reveal that shocks in petroleum prices and iron ore prices have a positive effect on stock returns in the first four to six months.

During the post-economic crisis period of 2016–2022, stock returns were mostly driven by the exchange rate (following its own shock). However, four of the five commodities also showed a larger percentage of the variation in stock returns, jointly accounting for about 35% of the variation in Month 4. As was the case during the economic crisis period, all five export commodities have made a much larger contribution to the variability of stock returns, with effects lasting about seven months. The impulse response functions for this period reveal that shocks in the petroleum price, iron ore price, soybean price, and poultry price have a positive effect on stock returns in the first three to four months. The results of this study are consistent with the findings of the studies by Wood, Idun, and Kawar (2024) [10], Tweneboah, Junior, and Kumah (2020) [4], Mensi, Hammoudeh, Shahzad, and Shahbaz (2017) [5], Salisu and Oloko (2015) [11], Mensi, Rehman, Hammoudeh, and Vo (2021) [8], and Manelli, Pace, and Leone (2024) [12]. Based on the results of this study, we can find evidence to conclude that stock returns in Brazil respond significantly to commodity price volatility. This response is more prominent during the 2014–2016 economic crisis in Brazil.

The results of the regression analysis show that during the entire study period of January 2010 to December 2022, prices of petroleum, iron ore, and sugar had a positive and statistically significant effect on the BVSP stock index. The price of soybeans had negative and statistically significant effect, while the price of poultry had a negative but insignificant effect on the BVSP stock index. During the pre-economic crisis period, prices of petroleum, iron ore, soybeans, and poultry had a positive effect, while the price of sugar had a negative effect on the BVSP stock index. During the economic crisis period, prices of petroleum, iron ore, and sugar had a positive effect, while prices of soybeans and poultry had a negative effect on the BVSP stock index. During the post-economic crisis period, prices of petroleum and iron ore had had a positive effect, while prices of sugar, soybeans, and poultry had a negative effect on the BVSP stock index. Based on the results of the regression analysis, we can find evidence to conclude that prices of petroleum and iron ore had a positive and significant effect, while the prices of sugar, soybeans, and poultry had mixed effects on the stock index. In addition, the S&P500 index showed a positive and statistically significant effect on the BVSP stock index in Brazil during all time periods.

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