Causality in Foreign Exchange Rates and Sugar Futures Prices for Brazil and South Africa

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ABSTRACT

This study examines the causal dynamic between raw sugar futures prices and nominal exchanges (USDZAR and USDBRL respectively) for the period 1 November 2016 to 31 October 2024. The world sugar number 11 contract for raw sugar was used as a proxy for raw sugar futures as both Brazil and South Africa are global suppliers of the commodity, and daily mid nominal exchange rates were used to track currency movements. Data was transformed into natural logarithms for homogeneity. An augmented Dickey-Fuller test confirmed that variables were non-stationary at their levels but achieved stationarity after first differencing. The Johansen cointegration test indicated that neither USDZAR nor USDBRL were found to have a long-run relationship with raw sugar futures prices, requiring the use of a vector autoregression (VAR) approach instead of vector error correction model (VECM) in our analysis.

Following the use of the VAR approach, we found that Granger-causality only runs in the direction from USDBRL to raw sugar futures prices, implying that short-term changes in raw sugar futures prices are influenced by currency movements in USDBRL; depreciation in USD against BRL has an increasing effect on raw sugar futures prices. A causal relation was not found for USDZAR and raw sugar futures prices. We connect this outcome to the currency-commodity framework which posits that currencies of dominant exporters of a commodity, such as Brazil, are influential on commodity prices because of the weight of the commodity's exports on its trade balance and terms of trade. For market participants and policy makers in Brazil, this outcome may be a useful early warning signal to aid in maximising sugar export returns.

KEYWORDS:

Commodities, raw sugar futures, exchange rates, causality, currency commodity

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LIST OF ACRONYMS

BBG	Bloomberg L.P.
BRL	Brazilian Real
CAD	Canadian Dollar
FX	Foreign exchange
ICE	Intercontinental Exchange
RBA	Reserve Bank of Australia
TOT	Terms of trade
US	United States of America
USD	United States Dollar
ZAR	South African Rand

CHAPTER 1. INTRODUCTION

1.1 Statement of purpose

This research is a quantitative study to determine direction of causality between nominal foreign exchange (FX) rates of Brazil and South Africa and world raw sugar futures prices.

Brazil and South Africa are among the leading players in global sugar production and raw sugar export (Sandrey, Vink, & Jensen, 2013), so understanding the dynamic between their exchange rates and sugar prices may be significant for formulating robust economic and trade policies, and for investors and companies with sugar exposure seeking to devise informed hedging and business strategies.

Through applying a Granger-causality test to time series data of nominal exchange rates and raw sugar futures prices, this research aims to provide insights into the predictive dynamics that could guide decision-making processes in the commodities and foreign exchange market.

1.2 Background of the study

The sugar market is a developing segment in the global agricultural construct, with over 100 countries involved in the cultivation of cane and beet sugar (Rumánková & Smutka, 2013). In financial markets, sugar is traded in the futures market, mainly through the Intercontinental Exchange (ICE) in New York through the sugar number 11 (NY#11) contract for raw sugar, and London through the sugar number 5 contract for refined sugar, serving as global benchmarking points for sugar prices and trading (Voora, Bermúdez, Le, Larrea, & Luna, 2023).

The type of sugar produced varies by country, with some specialising in either cane or beet sugar (Rumánková & Smutka, 2013), and some specialising in either raw sugar or refined sugar (Venon, 2023). Raw sugar, priced in United States dollar (USD) terms, is the most traded (Babirath, et al., 2021), and is the focus of this study as raw sugar-derived products have also evolved to non-consumption goods such as ethanol, which contribute to the demand of the commodity (Smutka, Pokorna, & Pulkrabek, 2011).

The sugar industry plays a critical role in the economic development and stability of the countries that produce it. Sugar from Brazil accounts for 40% of the world’s production, making it the largest, with the industry employing over 700,000 people (Voora, Bermúdez, Le, Larrea, & Luna, 2023). South Africa’s sugar industry is the largest in Africa, contributing to the country’s economy through positive socio-economic impact, gross domestic product, and FX export proceeds as raw sugar is priced in USD (Thibane, Soni, Phali, & Mdoda, 2023).

Despite the significant role the sugar industry plays, it experiences obstacles that challenge sustained fiscal viability, especially in the context of sugar prices and profitability of producers (Voora, Bermúdez, & Larrea, 2020). Sugar is one of the most volatile commodities to trade due to increasing demand that has an asymmetric relationship with the cyclical nature of production, while supply and demand dynamics influence global prices (Shaikh, 2015). The uncertainty in production levels and sugar prices places producers at risk as, historically, raw sugar prices have been below the cost of production (Haley, 2013; Shaikh, 2015; Voora, Bermúdez, & Larrea, 2020).

In the case of South Africa, structural inefficiencies resulting in inconsistent energy supply and irrigation (Dardagan, 2023), and a sugar tax called the Health Promotion Levy that is charged to sugar-sweetened beverage producers, have resulted in increased input costs for sugar producers, alongside reduced demand for sugar (Nicholson & Kadwa, 2023), which negatively impact returns. One of the leading sugar producing companies in the country went into business rescue while owing ZAR 800 million in export levies (Harper, 2024), reflecting the high costs associated with running a business that operates in the international market.

Brazil is expected to remain the leading sugar producer and exporter, but sugar producers do so at a cost, as high debt levels due to adverse weather conditions that impact crop output and returns lead to increasing bankruptcy rates (OECD, 2016). Although sugar production in major parts of Brazil is low-cost and efficient, as high yields are achieved with minimal irrigation, in dollar terms, historically, production costs have been increasing annually due to the appreciation of the Brazilian real (BRL) against USD in inflation-adjusted terms (Haley, 2013), which has made it a challenge for sugar producers to maintain their profit margins.

An increase in commodity prices offers improvements to the terms of trade (TOT) of commodity exporting countries, which may also offer improvements to the domestic exchange rate as they are typically priced in USD in the global market (Salisu, Adekunle, Alimi, & Emmanuel, 2019). Converting from USD to the domestic currency increases demand for the domestic currency, causing it to appreciate (Reserve Bank of Australia, 2005). These export proceeds may offer revenue gains to exporters, but the extent to which these gains can be realised also depends on how currencies trade (Reserve Bank of Australia, 2005).

Causality examines the ability to predict one variable using another (Wei, 2016). In the context of sugar prices and foreign exchange rates, being able to assess the causal relationship between the two may aid in forecasting the outcome of trading, investment, and hedging decisions, and commodity-related economic policy (Stern, 2004), potentially improving exporter and investment returns.

There is extensive research linking commodity prices and exchange rates for commodity exporting countries, but we did not find significant research explaining the relationship between sugar prices and exchange rates. Brazil and South Africa export raw sugar, therefore making it plausible that fluctuations in their exchange rates may have a link to changes in the raw sugar price.

1.3 Research problem

The dynamic between nominal exchange rates and raw sugar prices is underexplored to inform decision-making processes that might aid sugar exporters. Although Brazil and South Africa are leading raw sugar exporters, there is a notable absence of empirical research testing whether USDBRL or USDZAR causes N#11 sugar futures prices, leaving exporters without evidence-based hedging benchmarks. Accordingly, this research asks whether raw-sugar prices help predict BRL and ZAR movements, and whether the reverse holds.

1.4 Research questions

1.4.1 To what extent does a change in raw sugar prices predict fluctuations in the nominal exchange rates of Brazil Real (BRL) against USD and South Africa Rand (ZAR) against USD and/or vice versa?

1.4.2 What is the direction of causality between USDBRL and raw sugar prices, and USDZAR and raw sugar prices, if any?

1.5 Rationale

This research study is anticipated to inform aspects of decision-making and risk management practices within the sugar industry. By understanding the predictive dynamics between these economic variables, managers could refine their strategies for pricing, risk management during market volatility and financial planning. Additionally, the findings could support policymakers and regulatory bodies in the agricultural sector. An understanding of market dynamics and the impact on producers could guide the development of policies aimed at providing support mechanisms for producers.

Beyond practical implications, the study offers a theoretical contribution by addressing a gap in the literature on commodity-exchange rate interactions in emerging markets. By testing for Granger causality between USDBRL and USDZAR exchange rates and global futures prices, it extends empirical inquiry into transmission mechanisms between currency markets and commodity pricing – an area that remains underexplored for top sugar-exporting countries.

1.6 Delimitations of the study

1.6.1 The study is limited to Brazil and South Africa and results may not apply to other raw sugar exporting countries.

1.6.2 The only economic variables under consideration are raw sugar prices and nominal exchange rates.

1.6.3 The study will rely on secondary data. The accuracy of the results will be reliant on the completeness and reliability of the data source.

1.7 Research outline

This research is structured with Chapter 2 unpacking the literature review, with it comprised of two sections, namely a conceptual framework and theoretical framework. Chapter 3 is the methodology section, where time-series analysis is performed in two stages: the first being the Augmented Dickey-Fuller (ADF) and Johansen tests to determine whether the time-series variables under analysis are integrated and cointegrated, respectively: and the second stage is, if time series are cointegrated, a vector error correction model is used. Alternatively, if time series variables are not cointegrated, a vector autoregression in first differences is used to estimate the models. Granger causality tests are then conducted to determine the direction in which the variables influence each other. Chapter 4 explains the econometric results of the tests conducted, and Chapter 5 offers conclusions and further research recommendations.

CHAPTER 2. LITERATURE REVIEW

2.1 Introduction

This literature review will highlight the examined relationship between commodities and exchange rates and the theoretical framework that will underpin the econometric analysis. It is structured in three parts, beginning with (i) a conceptual foundation underpinned by exchange rate puzzles and the commodity-currency dynamic, (ii) a theoretical framework covering terms of trade and commodity-currency theories, and (iii) an empirical review that aims to highlight the gaps in literature relating to commodity and country specific causality studies.

2.2 Conceptual Framework

An extensive body of work exists on the relationship between exchange rates and commodity prices, and a few models have been referenced in the past to explain their behaviour. Although theories and models exist, global market dynamics have defied some of the purported logic.

2.2.1 Exchange rate disconnect puzzle and commodity prices

Meese and Rogoff (1983) pioneered earlier studies on predictive exchange rate modelling and the influence of macroeconomic fundamentals on exchange rates. Their original study did not find a relationship between macroeconomic fundamentals and exchange rates but rather proved that exchange rates followed a random walk model (Meese & Rogoff, 1983).

Subsequent research, sampling alternative data, found results that contradicted their conclusions, which gave rise to the phenomena of exchange rate puzzles, which are anomalies of exchange rate forecasting that underscore the limitations of models in their predictive capabilities (Mokoena, Gupta, & van Eyden, 2008). Sarno (2005) evaluated three of these puzzles, and in the case of the *exchange rate disconnect puzzle*, which argues that there is no correlation between exchange rates and macroeconomic variables, brings commodities into perspective and their impact on terms of trade (TOT). He rationalises that there is a link between commodity prices and exchange rates but may not apply universally to all commodity exporting countries due to differences in imports and exports.

2.2.2 Commodity prices and exchange rates

More recent studies have proven that commodity prices and exchange rates have a predictive effect on each other for commodity exporting countries.

Lui, Tan and Wang (2020), as an extension to the Meese-Rogoff exchange rate puzzle, examined the short-term forecastability of exchange rates by an index created from price changes in seventeen commodities for four commodity-exporting countries. Their results offer a robust counterargument and find that exchange rate forecastability using commodity prices is significant for countries reliant on commodity exports. Moreover, the study provides evidence that investment strategies informed by commodity price-change predictions yield higher returns (Liu, Tan, & Wang, 2020), providing practical financial implications of integrating commodity prices with exchange rates, but offers minimal guidance on the specific commodities driving the relationship.

Schaling, Ndlovu and Alagidede (2014) examined the hypothesis that ZAR moves in tandem with an IMF non-fuel commodity index using a Granger-causality test, and found a causal link in the direction of commodity prices having an impact on ZAR. They highlighted that a model for one currency cannot be fitted to another currency due to different levels of commodity dependency, agreeing with Sarno (2005), and suggested further research on the impact of individual commodities on exchange rates.

2.2.3 Causality studies on commodity prices and exchange rates

Causality testing was introduced by Granger (1969) as a fundamental approach to studying forecasting dynamics among time series. The test hypothesises that variable x causes variable y if the historical values of variable x are necessary to predict the historical values of variable y (Zhang, Dufour, & Galbraith, 2016). When assessing the causal linkage between two variables, the bivariate test estimates the following pair of regressions:

$$x_t = \beta_1 + \sum_{i=1}^{n} \propto_i y_{t-1} + \sum_{j=1}^{n} \delta_j x_{t-j} + u_{1t} \tag{1}$$

$$y_t = \beta_2 + \sum_{i=1}^{n} \rho_i y_{t-1} + \sum_{j=1}^{n} \varphi_j x_{t-j} + u_{2t} \tag{2}$$

Where β_1 and β_2 are intercepts, u_{1t} and u_{2t} are assumed to be unrelated white-noise terms, $\propto_i$ and φ_j are not 0, t is the current period, and t – j is the lag period.

Test outcomes can be distinguished as unidirectional causality from x to y or from y to x, bidirectional causality, and no causality, which would imply that the variables are independent from each other (Gujarati & Porter, 2009).

Commodity-specific causality studies have contextualised the predictive dynamics between commodity prices and exchange rates due to the varying levels of importance and economic contribution of commodities to different countries by offering insights on the direction of causality (Beckmann & Czudaj, 2013). In the case of the relationship between the price of oil and exchange rates of oil exporting countries, Granger-causality was found in the direction from exchange rates to oil prices for Brazil and Canada, where an appreciation in the Brazilian real and Canadian dollar is found to cause an increase in the oil price (Beckmann & Czudaj, 2013). Zhang, Dufour, & Galbraith (2016) extend this perspective in their Granger-causality study for copper, gold and oil for commodity-exporting Canada, Norway, Chile, and Australia, by considering multiple time horizons in both directions. Evidence of bidirectional causality was found for all countries, but causality was stronger from the direction of commodity prices to exchange rates at shorter time horizons.

Relational studies on sugar, as a commodity, and nominal exchange rates are limited from what we have found. A study focused on dependence analysis of the Brazilian sugar industry and the USDBRL nominal exchange rate using pair-copula constructions conducted by Resende and Candido (2015) found a long-run dependence and positive association between the two variables as Brazil is a net exporter of sugar, but did not determine direction of causality.

2.2.4 Futures contracts

Zapata, Fortenbery, and Armstrong (2005) determined that commodity futures prices play a critical role for exporters for pricing purposes as they are forward-looking, and that a hedge placed to manage risk using futures contracts results in stable and predictable outcomes. In a study on the risk management effectiveness of the raw NY#11 contract between 1990 and 2002, and its forecastability of the cash price of sugar, it was determined that its effectiveness was higher in the early 1990s, but wanes as we approach the latter years due to price shocks in the futures market (Zapata, Fortenbery, & Armstrong, 2005).

Chan, Tse, and Williams (2010) attribute the effectiveness of futures contracts to their price transparency, liquidity, high leverage, and the ability to sell the contract without owning the underling commodity, thus improving informational efficiency, which may be transmitted to currency markets. In their study on the relationship between commodity futures and exchange rate futures for Australia, Canada, New Zealand, and South Africa using country-specific commodity indices, they found no causal relationship in either direction on data with a 1-day frequency (Chan, Tse, & Williams, 2010). Their results differed from an earlier similar study that used quarterly data and alternative commodity indices that incorporated both commodity futures and forwards, but for Australia, New Zealand, South Africa, and Chile, and found a strong Granger-causality in the direction of exchange rates to commodity prices than in the opposite direction (Chen & Rogoff, 2003), highlighting the divergence in results caused by frequency of data, country, and commodity trading products.

2.3 Theoretical Framework

2.3.1 Aggregate-commodity framework

The overarching theoretical framework of this study is grounded in the aggregate-commodity terms of trade (TOT) theory. TOT is represented by the ratio of the price of exports to the price of imports and is thought to have an impact on exchange rates (Hamilton, 2018). When commodities are priced in a foreign currency, such as the

USD, higher commodity prices or increased demand can increase the foreign exchange supply to a commodity-exporting country due to higher export proceeds, leading to an appreciation of the domestic currency in the short term (Kohlscheen, Avalos, & Schrimpf, 2016). Alternatively, if commodities are priced in the domestic currency, an increase in demand will result in more of the domestic currency being required to purchase the commodity, causing the domestic currency to appreciate in the short term (Hamilton, 2018).

In the longer-term, favourable TOT can attract increased foreign direct investment to commodity exporting countries. This influx of investment can elevate aggregate demand, which may place upward pressure on inflation, potentially leading to higher domestic interest rates as well as a stronger exchange rate (Hamilton, 2018). This mechanism is typical of commodity-exporting countries, and price changes in these commodities are often used as a proxy for TOT changes (Kohlscheen, Avalos, & Schrimpf, 2016). Thus, in broad terms, the theory suggests that the prices of imports and exports of commodity-exporting countries and exchange rates may have a causal link.

Empirical analyses supported by the TOT theory has been on aggregate goods and commodities over longer-term horizons (Kohlscheen, Avalos, & Schrimpf, 2016; Hamilton, 2018). Although this perspective has been informative, it understates the day-to-day exchange rate movements in a single commodity market.

2.3.2 Single-commodity framework

A commodity currency is defined as one with significant commodity exposure and tends to strengthen when the export price of the commodity rises and weakens when the export price falls (Jeanneret & Sokolovski, 2023). The theory of a commodity currency narrows the idea that specific commodities can drive exchange rates when they constitute a significant portion of a country's export earnings (Chen & Rogoff, 2003) – the translation of USD-priced commodity export proceeds into local currency drives demand for the local currency, causing it to appreciate. To align with this study, the theory can be leveraged to refine the TOT theory by focusing on how, at a higher frequency of change (i.e. increase in price or increase in global demand), an individual export commodity price may potentially influence an exchange rate.

2.3.1 Single-currency framework

On the other hand, very few have highlighted the myopia of a single-currency framework, which mainly considers the influence of commodity prices on exchange rates. Clements and Fry (2006) propose a reciprocal currency-commodity framework wherein a commodity price is influenced by the currency movements of a single dominant producer or a group of dominant producers of a commodity. Using a multivariate latent factor model, they assessed three commodity currencies (Australian dollar, Canadian dollar and New Zealand dollar) against indices of food and beverages, metals, oils and agricultural material prices, and found a significant degree of influence from the direction of currencies to commodity prices, highlighting that models that do not consider the mutual influence between commodities and currencies, particularly where currencies may influence commodity prices, may be misspecified (Clements & Fry, 2006).

2.4 Gaps in the literature

Literature indicates further exploration needed in the lane of causality between exchange rates and soft commodities. Varied commodity indices and hard commodities such as metals and minerals seem to dominate the research sphere while raw sugar remains underexplored in relation to exchange rates. In the context of sugar and ethanol, Brazil appears occasionally in commodity studies, while South Africa frequents studies focused on mining and resource commodities, limiting country-specific insights in the context of raw sugar.

To underscore these gaps, Table 1 synthesises several recent Granger causality studies assessing soft commodities, their methodological approach, data frequency and direction of causality.

Table 1: Comparative Summary of Post-2016 Granger Causality Studies on Commodity and Exchange Rate Dynamics

Study	Country	Commodity	Method	Data Frequency	Direction of Causality	Sugar-Currency Link
Dlamini & Dlamini (2019)	Kingdom of Eswatini	Sugar	Todo-Yamamoto Granger	Annual	Exports → GDP	No
Obeng, et al. (2023)	Ghana	Cocoa, gold, crude oil	VECM, Granger	Monthly	Money supply ↔ commodity prices	No
Cermak & Ligocka (2022)	Global	Sugar, corn, cocoa, coffee, soybeans, wheat	ADF, Philips Peron, Granger	Daily	Commodity spot prices ↔ commodity futures prices	No
Micallef, Grima, Spiteri, & Rupeika-Apoga (2023)	United States of America	Sugar, wheat, corn, soybean, soybean oil, oats, rough rice, cotton, cocoa, coffee	ADF, Johansen cointegration, VAR model, Granger	Daily	Geopolitical risk → commodity prices	No
Murali, et al. (2018)	India	Sugar	ADF, Johansen cointegration, Granger	Monthly	Unidirectional price transmission India → London India → New York	No

From this comparative view, the following key gaps emerge:

1. There is a lack of linkage between sugar and currency in the studies, with none of them assessing a Granger-causal relationship between sugar prices and nominal exchange rates, particularly at daily frequency. The studies either focus on the dynamic between sugar exports (Dlamini & Dlamini, 2019), the dynamic between commodity spot and futures markets (Cermak & Ligocka, 2022), or dynamic between geopolitical risk and commodity prices (Micallef et al., 2023).
2. There is an underrepresentation of Brazil and South Africa in these studies, and where sugar is included in the studies, it is often grouped with other

commodities, limiting understanding of how exchange rate dynamics present in different sugar exporting markets.

3. The findings in the studies also do not link to hedging or pricing strategies for sugar exporters and related parties.

By modelling Granger-causal relationships between raw sugar futures prices and daily nominal exchange rates for Brazil and South Africa, and building on calls from Sarno (2005) and Schaling, Ndlovu, & Alagidede (2014) to make the studies country and commodity specific, this study aims to address an evident gap in the commodity-currency literature. As well to contribute to existing literature to guide on hedging and policy strategies for raw sugar exports in Brazil and South Africa.

2.5 Hypotheses

In the case of raw sugar prices and leading producers Brazil and South Africa, the hypotheses to be tested can thus be stated as:

H_{01}: Changes in the daily nominal exchange rates of Brazil and South Africa do not Granger-cause changes in the daily raw sugar prices.

H_{02}: Changes in the daily raw sugar prices do not Granger-cause changes in the daily nominal exchange rates of Brazil and South Africa.

H_{03}: There is no bidirectional causality between the daily nominal exchange rates of Brazil and South Africa and daily raw sugar prices.

CHAPTER 3. RESEARCH METHODOLOGY

3.1 Introduction

This study adopted a quantitative research approach that aimed to examine the potential causal relationship between raw sugar futures prices and nominal exchange rates for Brazil and South Africa from 1 November 2016 to 31 October 2024.

3.2 Research design

This study followed a longitudinal and non-experimental design as in-sample secondary time series data was observed to examine causal linkages.

3.3 Data

3.3.1 Data source

Bloomberg L.P. (BBG) was used as a data source as it publicly provides historical prices and rates of the variables being studied for the required frequency and time horizon (Tee, 2024), offering reliability, replicability, and verification of the findings. Stata was used as the statistical software to analyse the time series data.

3.3.2 Time series variables

Daily mid nominal exchange rates for USDBRL and USDZAR, and daily mid sugar no. 11 futures (NY#11) contract price data was collected from BBG historical price database from 1 November 2016 to 31 October 2024. This time horizon was chosen due to limited raw sugar no. 11 futures price data. Daily data was used to capture the short-term market dynamics and identify nuanced patterns and relations due to its high frequency and high number of observations (Negrini de Mattos & Corrêa, 2023).

The NY#11 contract is the global benchmark contract for raw sugar trading, is priced in USD, and establishes the price for the physical delivery of raw cane sugar, free-onboard the recipient's desired method of transportation to a shipping port within one of the 30 originating countries, which include Brazil and South Africa (ICE, 2024). This choice of variable was appropriate as the price reflects market dynamics, liquidity, macroeconomic factors, policy changes and geopolitical events as they relate to the sugar market (Negrini de Mattos & Corrêa, 2023). As it is also priced in USD, it was appropriate as proxy for raw sugar prices and for analysis against the nominal exchange rates of USDZAR and USDBRL.

The sample data was selected as guided by the research and variables in question, as well as availability of uncompromised and consistent time series data. All data values was converted to natural logarithms for homogeneity.

Time series variables will, thus, be indicated as follows:

- lnZAR: natural logarithm of daily mid nominal USDZAR exchange rate
- lnBRL: natural logarithm of daily mid nominal USDBRL exchange rate
- lnSFP: natural logarithm of daily mid raw sugar futures price

3.3.3 Missing data

Historical daily mid rates and prices from BBG for USDBRL, USDZAR and the NY#11 contract are only available for business days, with no reference rates or prices for non-trading days such as holidays and weekends. Daily data completeness for one of the econometric methods (i.e. Johansen cointegration test) is a Stata software requirement. To maintain continuity, each missing weekend and holiday data point was linearly interpolated using the preceding and following non-missing observations. Linear interpolation is effective in addressing small data gaps as changes between daily data points are gradual, maintaining the short-term dynamics of the original time series (Pathirage & Tallozy, 2024).

3.4 Econometric methods

Causality was examined through the application of the following econometric models and tests that have been extensively used in literature to study this dynamic between variables.

3.4.1 Unit root test for non-stationarity in time series

The augmented Dickey-Fuller (ADF) unit root test assesses whether time series is non-stationary by testing the null hypothesis of the presence of a unit root. Stationarity implies that the statistical properties of time series data, such as the mean, variance, and autocorrelation, are constant over time, enhancing its validity of statistical inference for modelling and forecasting (Kumar, 2023). The presence of a unit root indicates that the series followed a stochastic trend and was therefore non-stationary, which can lead to spurious regression and misleading results. Therefore, any non-stationary time series data should be differenced *d* times until stationarity is reached to make the time series I(*d*), i.e. integrated of order *d* (Tsegaye, 2015).

The model used for each time series:

$$\Delta\eta_t = \alpha + \beta\eta_{t-1} + \sum_{i=1}^{n} \gamma_i \, \Delta\eta_{t-i} + \varepsilon_t \qquad (3)$$

Where:

$\Delta\eta_t = \eta_t - \eta_{t-1}$ is the difference between time series data points at time t

α is the intercept

β is the coefficient for the lagged value of the time series

γ_i is the coefficient of the lagged difference terms

ε_t is the error term at time t

And the null hypothesis, H_0 is $\beta = 0$ for presence of a unit root and non-stationarity, and the alternative hypothesis, H_1 is $\beta \neq 0$ for no unit root and stationarity in the respective time series.

3.4.2 Johansen cointegration test

When non-stationarity is determined at lnZAR, lnBRL and lnSFP level data, a Johansen (1987) cointegration test followed differencing to assess the long-run equilibrium relationship between variable pairs lnZAR and lnSFP, and lnBRL and lnSFP. In this case, two variables are considered cointegrated when they are individually integrated of the same order and their linear combination is stationary. The cointegrated variables do not drift too far apart over time and tend to revert to their long-run equilibrium (Ssekuma, 2011). The Johansen cointegration test is considered a robust assessment of cointegration, and data validity, as it allows multiple cointegrating relationships and includes an error correction term which tells us how the variables adjust and return to equilibrium (Brooks, 2014).

3.4.3 Vector error correction

If the time series are cointegrated, there exists short-run and long-run equilibrium in how lnZAR and lnSFP and lnBRL and lnSFP relate to each other. When short-run deviations from equilibrium are experienced, the vector error correction model (VECM) illustrates the rate at which long-run equilibrium is restored using an error correction term (Schaling, Ndlovu, & Alagidede, 2014).

When assessing the causal linkage between two variables, the test estimated the following pairs of regressions from (1) and (2) to assess causality in both directions. For lnZAR and lnSFP:

$$lnZAR_t = \beta_1 + \sum_{i=1}^{n} \propto_i lnSFP_{t-i} + \sum_{j=1}^{n} \delta_j \, lnZAR_{t-j} + u_{1t} \tag{4}$$

$$lnSFP_t = \beta_2 + \sum_{i=1}^{n} \rho_i lnSFP_{t-i} + \sum_{j=1}^{n} \varphi_j \, lnZAR_{t-j} + u_{2t} \tag{5}$$

As well as lnBRL and lnSFP:

$$lnBRL_t = \beta_1 + \sum_{i=1}^{n} \propto_i lnSFP_{t-i} + \sum_{j=1}^{n} \delta_j \, lnBRL_{t-j} + u_{1t} \tag{6}$$

$$lnSFP_t = \beta_2 + \sum_{i=1}^{n} \rho_i lnSFP_{t-i} + \sum_{j=1}^{n} \varphi_j \, lnBRL_{t-j} + u_{2t} \tag{7}$$

Where β_1 and β_2 are intercepts, u_{1t} and u_{2t} are unrelated white-noise terms, $\propto_i$ and φ_j are not 0, t is the current time period, t – i and t – j are the lag periods, and n is the maximum lag length.

Where there was differencing in the data to reach stationarity, the VECM was derived from (4) to (7) and is represented as below for ∆lnZAR and ∆lnSFP:

$$\Delta lnZAR_t = \beta_1 + \nu_1 ECT_{1t-1} + \sum_{i=1}^{n} \propto_i \Delta lnSFP_{t-i} + \sum_{j=1}^{n} \delta_j \Delta lnZAR_{t-j} + u_{1t} \quad (8)$$

$$\Delta lnSFP_t = \beta_2 + \nu_2 ECT_{2t-1} + \sum_{i=1}^{n} \rho_i \Delta lnSFP_{t-i} + \sum_{j=1}^{n} \varphi_j \Delta lnZAR_{t-j} + u_{2t} \quad (9)$$

And for ∆lnBRL and ∆lnSFP:

$$\Delta lnBRL_t = \beta_1 + \nu_1 ECT_{1t-1} + \sum_{i=1}^{n} \propto_i \Delta lnSFP_{t-i} + \sum_{j=1}^{n} \delta_j \Delta lnBRL_{t-j} + u_{1t} \quad (10)$$

$$\Delta lnSFP_t = \beta_2 + \nu_2 ECT_{2t-1} + \sum_{i=1}^{n} \rho_i \Delta lnSFP_{t-i} + \sum_{j=1}^{n} \varphi_j \Delta lnBRL_{t-j} + u_{2t} \quad (11)$$

Where ν_1 and ν_2 are coefficients of the error correction ECT that reflects adjustments to the long-run equilibrium.

3.4.4 Vector autoregression

If the time series are not cointegrated, meaning they do not have both stable short-run and long-run relationships, a vector autoregression model can be determined in the variables' differences. Unlike VECM, in the absence of cointegration, the model focuses on the short-run interactions amongst variables and excludes error correction terms as there are none to correct to in the long-run.

When assessing the causal linkage between two variables, the test also estimated the pairs of regressions from (1) and (2) to assess causality in both directions. If variable x_t and y_t are integrated of order *1* (i.e. I(*1*)), and not cointegrated, in their first differences:

$$\Delta x_t = \beta_1 + \sum_{i=1}^{p} \propto_{1i} \Delta x_{t-i} + \sum_{j=1}^{p} \varphi_{1j} \Delta y_{t-j} + u_{1t} \quad (12)$$

$$\Delta y_t = \beta_2 + \sum_{i=1}^{p} \propto_{2i} \Delta y_{t-i} + \sum_{j=1}^{p} \varphi_{2j} \Delta x_{t-j} + u_{2t} \quad (13)$$

Where Δx and Δy variable x and y in their first difference, p is the lag order (from AIC and HQIC criteria), β_1 and β_2 are the intercepts, u_{1t} and u_{2t} are the error terms, and $\propto_{1i}$, $\propto_{2i}$, φ_{1j}, and φ_{2j} are the estimated parameters.

Applying (12) and (13) to lnZAR and lnSFP:

$$\Delta lnZAR_t = \beta_1 + \sum_{i=1}^{p} \propto_{1i} \Delta lnZAR_{t-i} + \sum_{j=1}^{p} \varphi_{1j} \Delta lnSFP_{t-j} + u_{1t} \quad (14)$$

$$\Delta lnSFP_t = \beta_2 + \sum_{i=1}^{p} \propto_{2i} \Delta lnSFP_{t-i} + \sum_{j=1}^{p} \varphi_{2j} \Delta lnZAR_{t-j} + u_{2t} \quad (15)$$

And (12) and (13) to lnBRL and lnSFP:

$$\Delta lnBRL_t = \beta_1 + \sum_{i=1}^{p} \propto_{1i} \Delta lnBRL_{t-i} + \sum_{j=1}^{p} \varphi_{1j} \Delta lnSFP_{t-j} + u_{1t} \quad (16)$$

$$\Delta lnSFP_t = \beta_2 + \sum_{i=1}^{p} \propto_{2i} \Delta lnSFP_{t-i} + \sum_{j=1}^{p} \varphi_{2j} \Delta lnBRL_{t-j} + u_{2t} \quad (17)$$

The VAR approach complements the VECM as it allows for causality analysis in the absence of cointegration by determining whether the lagged variables in their differences can significantly predict the other.

3.4.5 Granger causality

If the coefficients $\propto_i$ were significantly nonzero as generally illustrated in (1) and (2), we can conclude that y "Granger-causes" x. And if the coefficients φ_j were significantly nonzero as generally illustrated in (1) and (2), we can conclude that x "Granger-causes" y.

From assessing the parameter estimates from either (8), (9), (10), (11) or parameter estimates from (14), (15), (16), (17), based on whether the variables are cointegrated or not, we perform tests with hypotheses:

i. H_0: $\propto = 0$, H_1: $\propto \neq 0$
ii. H_0: $\varphi = 0$, H_1: $\varphi \neq 0$

Failure to reject both hypotheses will indicate that there is no significant bidirectional Granger-causal relationship between raw sugar futures prices and USDZAR and USDBRL respectively.

3.5 Possible limitations and challenges of the study

- NY#11 and nominal exchange rate data may be inconsistent across data sources, which may affect reliability of analysis.
- The range and frequency of the data may not fully capture the causal dynamics between the variables.
- Results may not generalise well to out-of-sample predictions as only in-sample data was considered.

3.6 Quality assurance

3.6.1 Internal validity

An Augmented Dickey-Fuller test was conducted to confirm that time series are stationary to avoid spurious results (Kumar, 2023).

3.6.2 External validity

The results may not be generalizable due to literature indicating that the relationship between exchange rates and commodity prices may not apply universally to all commodity-exporting countries and commodities (Sarno, 2005).

3.6.3 Reliability

The accuracy of the results of the Granger-causality test has a strong dependence on the lag length used, therefore the use of the Akaike Information Criterion (AIC) and Hannan-Quinn Information Criterion (HQIC) assisted in confirming the appropriate lag to use (Schaling, Ndlovu, & Alagidede, 2014).

3.7 Ethical considerations

This quantitative study followed the Wits University ethical guidelines in terms of using secondary data. The secondary data considered is publicly available and appropriately referenced.

CHAPTER 4. ECONOMETRIC RESULTS

The time series were transformed into natural logarithms (lnZAR, lnBRL, lnSFP) to smoothen the values and reduce outliers that may skew the results to create spurious regressions. Figure 1 illustrates that lnZAR and lnBRL exhibit a somewhat upward trend, but do not hover around the same mean as lnSFP.

Figure 1: Natural logarithm of USDZAR, USDBRL and SFP from November 2016 to October 2024

Source: Author's graphing using Stata

Table 2 reports the pairwise regressions between the exchange rates and lnSFP. Although transforming the time series into natural logarithms was intended to reduce heteroskedasticity, the regression results suggest a high likelihood of spurious regression. The coefficient of determination (R^2) for each pair of regressions exceeds 0.15 and the Durbin-Watson d-statistics are low. Granger and Newbold's (1974) rule of thumb is if R^2 > Durbin-Watson d-statistic, it is a strong warning sign of spuriousness, implying that the regression equations may have a misleading degree of fit.

Table 2: Coefficient of determination (R^2) and Durbin-Watson d-statistics

x, y	R^2	Durbin-Watson d-statistic
lnZAR, lnSFP	0.2945	0.0058919
lnSFP, lnZAR	0.2945	0.0054198
lnBRL, lnSFP	0.1514	0.0023893
lnSFP, lnBRL	0.1514	0.0036553

Source: Author's Stata calculations

Therefore, transforming the time series data into natural logarithms does not guarantee stationarity. This warrants the next steps of conducting unit root tests for stationarity, cointegration analysis and determining causal inferences.

4.1 Unit root test for stationarity in time-series

The augmented Dickey-Fuller test is employed to test for the null hypothesis of a unit root**.** The optimal lag length was determined using AIC and HQIC. A lag length of 2 was selected as it minimised both information criteria (AIC = -19.9935, HQIC = -19.9784), as seen in Appendix A1, supporting a VAR(2) model specification, with results compared across multiple lags. If a time series is non-stationary and has a unit root at its level, it needs to be differenced *d* number of times until it reaches stationarity. Table 3 illustrates the summary of results of the ADF unit root test for all three variables. Results are accepted at the 5% level of significance.

Table 3: ADF unit root and stationarity test with constant and trend*

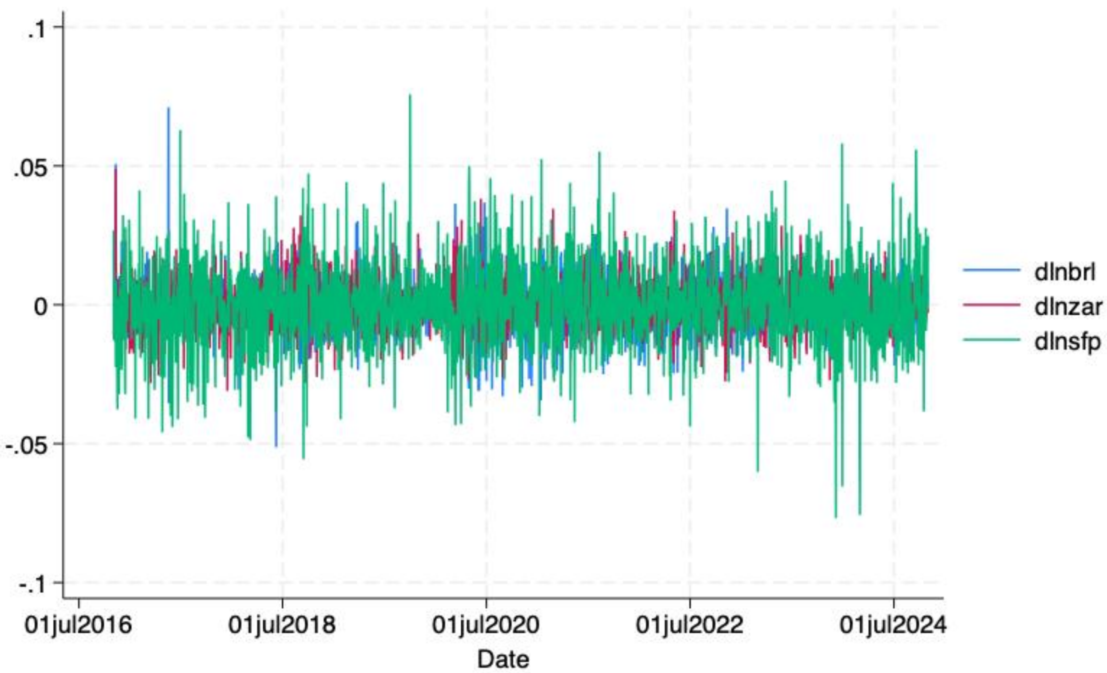
Variable	Form	Z(t) - Test statistic	P-value	Conclusion
lnZAR	Level	-3.1200	0.0992	Non-stationary
	First difference	-30.872	0.0000	Stationary
lnBRL	Level	-1.9670	0.6190	Non-stationary
	First difference	-30.801	0.0000	Stationary
lnSFP	Level	-3.1710	0.0904	Non-stationary
	First difference	-29.037	0.0000	Stationary

**Augmented Dickey-Fuller critical values at 1%, 5% and 10% are -3.96, -3.41 and -3.12*
Source: Author's Stata calculations

The null hypothesis of a unit root cannot be rejected at the 1%, 5% and 10% levels of significance for lnBRL. The test statistic is greater than all three critical values, indicating that the variable is non-stationary at its level and requires differencing. Although the test statistics for lnZAR and lnSFP exceed the critical value at the 10% significance level, the null hypothesis of a unit root cannot be rejected at the 5% significance level, with the test statistics at -3.12 and -3.1271 and p-values at 0.0992 and 0.0904 respectively. Both time series are non-stationary at their levels and require differencing.

After first differencing, all three timeseries are concluded as stationary, with the null hypothesis of a unit root rejected at the 5% significance level. The results indicate that lnZAR, lnBRL and lnSFP are I(1) (integrated of order 1) at level and I(0) (integrated of order zero) after first differencing. Figure 2 illustrates the variables in their first differences, i.e., $\Delta\ln\text{ZAR}$, $\Delta\ln\text{BRL}$ and $\Delta\ln\text{SFP}$, fluctuating around zero – a suggestion of stationarity and that spurious regressions are likely to be avoided.

Figure 2: First difference of natural logarithm of USDZAR, USDBRL and SFP from November 2016 to October 2024



Source: Author's graphing using Stata

4.2 Johansen cointegration test

The results of the ADF unit root test proved that lnZAR, lnBRL, and lnSFP variables are all stationary after first differencing, necessitating a cointegration test.

We first applied the Johansen cointegration test on lnZAR and lnSFP. With only two variables used in the test, the output generated, at most, a single cointegrating vector. The null hypothesis of the test is that the rank of the matrix is zero, i.e. there is no cointegrating relationship. The alternative hypothesis is that the rank is 1, suggesting a cointegrating relationship.

Table 4 shows that both the trace statistic and maximum eigenvalues are less than the 5% critical values. At rank 1, both the trace statistic and maximum eigenvalues are less than the 5% critical values. Consequently, we fail to reject the null of no cointegrating relationship and conclude that there is no long-run equilibrium relationship between the USDZAR exchange rate and the raw sugar futures price.

Table 4: Johansen cointegration test for lnZAR and lnSFP with constant

Rank	Trace statistic	5% Critical value	Maximum Eigenvalue	5% Critical value
*0	10.9114	15.41	9.9899	14.07
1	0.9215	3.76	0.9215	3.76

** states the number of maximum cointegration vectors*
Source: Author's Stata calculations

The Johansen cointegration test was also applied on lnBRL and lnSFP with results shown in Table 5. At rank 0, both the trace statistic and maximum eigenvalues are less than the 5% critical values, and the same holds at rank 1. Consequently, we fail to reject the null of no cointegrating relationship and conclude that there is no long-run equilibrium relationship between USDBRL exchange rate and the raw sugar futures price.

Table 5: Johansen cointegration test for lnBRL and lnSFP with constant

Rank	Trace statistic	5% Critical value	Maximum Eigenvalue	5% Critical value
*0	12.7738	15.41	11.2214	14.07
1	1.5524	3.76	1.5524	3.76

** states the number of maximum cointegration vectors*
Source: Author's Stata calculations

In summary, neither of the pair of variables – lnZAR and lnSFP and lnBRL and lnSFP - display stable long-run behaviour. Lack of cointegration could stem from the sampling period which spans the COIVD-19 period and its varying disruptions across asset classes, impacting any long-run equilibrium behaviour. As well the fact that this raw sugar is priced in USD and its volatility differs from that of the local currencies.

Therefore, any modelling of these variables should be done where the variables are I(0), which is in their first differences. We, thus, disregard VECM estimation and proceed with VAR model estimation.

4.3 VAR model estimation in first differences

Tables 5 and 6 illustrate the results of the VAR(2) model for $\Delta\ln\mathrm{ZAR}$ and $\Delta\ln\mathrm{SFP}$, corresponding to equations (15) and (14) respectively. Coefficient estimates are evaluated at a 5% significance level. Table 6 shows estimates of the model of $\Delta\ln\mathrm{SFP}$ as the dependent variable. The first lag of $\Delta\ln\mathrm{SFP}$ is positive and significant, suggesting that if the sugar futures price rises on one day, it tends to continue rising the next day. By contrast, the first lag of $\Delta\ln\mathrm{ZAR}$ has a negative coefficient and is not statistically significant with a p-value of 0.088. The second lags of both $\Delta\ln\mathrm{ZAR}$ and $\Delta\ln\mathrm{SFP}$ explanatory variables are statistically insignificant and indicate that they have no influence on changes in the raw sugar futures price.

Table 6: Raw sugar futures price as dependent variable

Independent variable intercept		Regression coefficient	Z-value	P-value	Lower 95% confidence level	Upper 95% confidence level
		0.000024	0.10	0.922	-0.0004544	0.0005024
$\Delta \ln SFP_{t-i}$	Lag 1	0.0885361	4.77	0.000	0.0521605	0.1249117
	Lag 2	0.0249186	1.34	0.179	-0.0114161	0.0612533
$\Delta \ln ZAR_{t-i}$	Lag 1	-0.0562206	-1.71	0.088	-0.1207654	0.0083243
	Lag 2	0.0068300	0.21	0.836	-0.0577264	0.0713864

Source: Author's Stata calculations

Estimated model:

$\Delta lnSFP_t = 0.000024 + 0.0885361\Delta lnSFP_{t-1} + 0.0249186\Delta lnSFP_{t-2} - 0.0562206\Delta lnZAR_{t-1} + 0.00683\Delta lnZAR_{t-2}$

Table 7 shows the estimated coefficients for the equation in which $\Delta \ln ZAR$ is the dependent variable. Both lags of $\Delta \ln SFP$ are statistically insignificant, with p-value 0.975 for the first lag and 0.778 for the second lag, indicating that previous day changes in raw sugar futures prices do not explain changes in the USDZAR exchange rate. The first lag of the $\Delta \ln ZAR$ is positive and statistically significant at the 5% level, with a p-value that is less than 0.01. This suggests that USD appreciation against ZAR in one day tends to continue into the next day. The second lag is statistically insignificant with a p-value of 0.931, indicating no influence on USDZAR exchange rate. Both sets of results suggest that South African sugar exporters sugar price forecasts should not be informed by USDZAR exchange rate movements or the other way around. Hedging strategies should consider broader macroeconomic factors influencing both variables.

Table 7: USDZAR exchange rate as dependent variable

Independent variable intercept		Regression coefficient	Z-value	P-value	Lower 95% confidence level	Upper 95% confidence level
		0.0000857	0.62	0.533	-0.0001839	0.0003553
$\Delta \ln SFP_{t-i}$	Lag 1	0.0003257	0.03	0.975	-0.0201745	0.0208260
	Lag 2	-0.0029429	-0.28	0.778	-0.0234201	0.0175343

$\Delta\ln ZAR_{t-i}$	Lag 1	0.0649467	3.50	0.000	0.0285711	0.1013223
	Lag 2	0.0016019	0.09	0.931	-0.0347803	0.0379840

Source: Author's Stata calculations

Estimated model:

$\Delta lnZAR_t = 0.0000857 + 0.0649467\Delta lnZAR_{t-1} + 0.0016019\Delta lnZAR_{t-2} + 0.0003257\Delta lnSFP_{t-1} - 0.0029429\Delta lnSFP_{t-2}$

Tables 8 and 9 display the results of the VAR(2) model for $\Delta\ln BRL$ and $\Delta\ln SFP$. Table 8 shows estimates of the model for $\Delta\ln BRL$. Both lags of $\Delta\ln SFP$ have negative regression coefficients and are statistically insignificant with p-values exceeding the 5% level of significance. This suggests that raw sugar futures price changes have little influence on USDBRL exchange rate. Similarly, the regression coefficients of $\Delta\ln BRL$ are also negative and statistically insignificant (p-value > 0.05), indicating that changes in the USDBRL exchange in one period have no meaningful impact on changes in the subsequent period.

Table 8: USDBRL exchange rate as dependent variable

Independent variable intercept		Regression coefficient	Z-value	P-value	Lower 95% confidence level	Upper 95% confidence level
		0.0001908	1.38	0.167	-0.0000801	0.0004616
$\Delta\ln SFP_{t-i}$	Lag 1	-0.0025203	-0.24	0.812	-0.0233281	0.0182875
	Lag 2	-0.0075499	-0.71	0.475	-0.0282845	0.0131847
$\Delta\ln BRL_{t-i}$	Lag 1	0.0096116	0.51	0.608	-0.0270804	0.0463035
	Lag 2	0.0303328	1.62	0.106	-0.0064305	0.0670962

Source: Author's Stata calculations

Estimated model:

$\Delta lnBRL_t = 0.0001908 - 0.0025203\Delta lnSFP_{t-1} - 0.0075499\Delta lnSFP_{t-2} + 0.0096116\Delta lnBRL_{t-1} + 0.0303328\Delta lnBRL_{t-2}$

Table 9 illustrates the results where $\Delta \ln SFP$ is the dependent variable. For $\Delta \ln SFP$, the first lag has a positive regression coefficient and is statistically significant (p-value < 0.01), which indicates that an increase in the sugar futures price in one day tends to continue into the next day. This is a similar outcome as illustrated in Table 6, which alludes to a first-lag persistence in raw sugar futures prices. The same cannot be said about the second lag that is statistically insignificant with a p-value of 0.306, indicating that positive changes in the price of sugar futures prices in one day do not continue two days later.

Table 9: Raw sugar futures price as dependent variable

Independent variable intercept		Regression coefficient	Z-value	P-value	Lower 95% confidence level	Upper 95% confidence level
		0.0000556	0.23	0.820	-0.0004220	0.0005331
$\Delta \ln SFP_{t-i}$	Lag 1	0.0785388	4.20	0.000	0.0418522	0.1152254
	Lag 2	0.0190890	1.02	0.306	-0.0174686	0.0556466
$\Delta \ln BRL_{t-i}$	Lag 1	-0.1127467	-3.42	0.001	-0.1774389	-0.0480545
	Lag 2	-0.0693194	-2.10	0.036	-0.1341376	-0.0045012

Source: Author's Stata calculations

Estimated model:

$$\Delta lnSFP_t = 0.0000556 + 0.0785388\Delta lnSFP_{t-1} + 0.019089\Delta lnSFP_{t-2} - 0.1127467\Delta lnBRL_{t-1} - 0.0693194\Delta lnBRL_{t-2}$$

For $\Delta \ln BRL$, both lags are negative and statistically significant, with p-value 0.001 for lag 1 and 0.036 for lag 2 respectively. This suggests that when USD weakens (BRL strengthens) for two consecutive days, the USD price of raw sugar futures tends to increase the next day. In more practical terms, if, for instance, USDBRL weakens (i.e. USD depreciates, BRL appreciates) by 1%, in one day, raw sugar futures prices may increase by 0.11% (0.1% x 0.1127467) on the second day, suggesting a firmer BRL against USD makes raw sugar exports expensive for importers. This can have the effect of dampening demand for Brazilian raw sugar in the short-term, and then later weakening raw sugar's USD-denominated price. This aligns with the commodity-currency framework that suggests that changes in commodity currency exchanges rates can feed into the USD-denominated price of the commodity in focus. Brazilian sugar exporters should actively monitor USDBRL volatility when timing future sales or entering hedging contracts.

4.4 Granger causality test

We tested the null hypothesis that y does not "Granger-cause" x or x does not "Granger-cause" y at the chosen lag length of 2 and daily data frequency. Specifically, in the case of equation (12), we assessed whether coefficients of the lagged terms of y are jointly different from zero (i.e. statistically significant at the 5% level of significance).

4.4.1 Causality from lnZAR to lnSFP

Results from Table 5 show that coefficients of $\Delta lnSFP$ and $\Delta lnZAR$ are not statistically significant at the 5% level. We, therefore, fail to reject the null hypothesis and conclude that $\Delta lnZAR$ does not Granger-cause $\Delta lnSFP$.

4.4.2 Causality from lnSFP to lnZAR

Similarly, as shown in Table 6, for lnSFP to lnZAR, the coefficients of $\Delta lnSFP$ are statistically insignificant with p-values 0.975 and 0.778 for lag 1 and 2 respectively. We fail to reject the null hypothesis and conclude $\Delta lnSFP$ does not Granger-cause $\Delta lnZAR$. We holistically conclude that there is no Granger-causal relationship in either direction of lnZAR and lnSFP.

4.4.3 Causality from lnSFP to lnBRL

Results from Table 7 show that coefficients of $\Delta lnSFP$ and $\Delta lnBRL$ are not statistically significant at the 5% level. We, therefore, fail to reject the null hypothesis and conclude that $\Delta lnSFP$ does not Granger-cause $\Delta lnBRL$.

4.4.4 Causality from lnBRL to lnSFP

Similarly, shown in Table 8, for lnBRL to lnSFP, the coefficients of $\Delta lnBRL$ are statistically significant with p-values 0.001 and 0.036 for lag 1 and 2 respectively. We reject the null hypothesis and conclude $\Delta lnBRL$ Granger-causes $\Delta lnSFP$, and, therefore, conclude that there is a unidirectional Granger-causal relationship in the direction of lnBRL to lnSFP. Short-term sample period changes in USDBRL have a predictive effect on raw sugar futures price changes. This outcome aligns with a currency-commodity framework for Brazil and implies that fluctuations in USDBRL shape raw sugar prices.

CHAPTER 5. CONCLUSION AND FURTHER RESEARCH RECOMMENDATIONS

This paper intended to study the causal linkage between raw sugar prices and exchange rates, particularly USDBRL and USDZAR, with Brazil and South Africa as key exporters of the commodity. The daily sugar number 11 futures prices and daily nominal exchange rates were used as proxies.

5.1 Key findings and economic interpretation

The study neither found a long-run cointegrating relationship between daily nominal exchange rates and raw sugar futures prices over the sample eight-year period, nor did it find a dependent relationship between USDZAR and raw sugar futures prices in the short-run in either direction. However, a unidirectional Granger-causal relationship was determined to exist from the daily USDBRL nominal exchange rate to the daily raw sugar futures prices – suggesting that short-term fluctuations in USDBRL can be used to predict raw sugar price movements.

From an economic standpoint, as concluded in chapter 4, the coefficient of -0.11 on the first lag of $\Delta \ln \mathrm{BRL}$ in the VAR model where raw sugar futures prices are the dependent variable suggests that a 1% appreciation of BRL against USD raises raw sugar futures prices by 0.11% in the short run. This aligns with Clements & Fry's (2006) theory of a currency-commodity dynamic, where dominant commodity currencies influence that commodity's pricing on a global scale. It also affirms the commodity-currency argument by Chen & Rogoff (2003) and Sarno (2005) that the strength of this linkage is tied to the country's market share of the commodity and its trade balance weighting.

5.2 Implications for exporters and policymakers

The sugar industry plays a critical role in the Brazilian economy, accounting for 40% of global sugar production, with the country being the leading global exporter (Voora, Bermúdez, Le, Larrea, & Luna, 2023).

For South African sugar exporting firms, and market participants who may hold similar exposures, insights that can be drawn are that there is minimal gain in understanding the predictive nature between USDZAR and raw sugar prices, especially where their financial performance may be concerned. This is in line with them not being a dominant market player in the raw sugar producing and exporting market. However, leveraging FX market signals from how USDBRL trades, as it has a causal impact on raw sugar prices, could influence their returns positively. Entering raw sugar futures contracts at optimal levels (i.e. selling raw sugar for future delivery at a favourable predetermined price) and foreign currency forward or option contracts could aid in maximising profit margins from the translation gains to be realised in the sale of USD for the local currency ZAR. This could have the effect of increasing supply for USD and increasing demand for ZAR. This ties back to the TOT framework which implies that commodity currency demand can increase from the sale of USD-priced commodities (Kohlscheen, Avalos, & Schrimpf, 2016).

For Brazilian sugar exporting firms, and market participants who may hold similar exposures, fluctuations in USDBRL can be used as an early warning signal for raw sugar price movements. Through effective risk management practices, returns can be maximised through the strategic timing of placing FX hedges to translate USD into BRL from export proceeds. Policymakers in this market may find that monitoring USDBRL trading may aid in supporting the local agricultural sector and consider the potential impact on raw sugar export income when making monetary and fiscal policy decisions that may adversely move the local currency.

5.3 Theoretical relevance and contribution

Brazil and South Africa are both global raw sugar exporters. This study confirms that a single model cannot be universally applied to commodity currencies, especially when the commodity in question does not contribute to each country's trade balance and TOT in the same weight. This aligns with our result of no causal relationship between USDZAR and raw sugar prices relative to a unidirectional causal relationship from USDBRL to raw sugar prices. It is also consistent with Sarno (2005), who, in the context of this study, implies that raw sugar exporters should not be viewed the same. Chen & Rogoff (2003), Liu, Tan, & Wang (2020), and Clements & Fry (2006) echo the same sentiment, with studies that highlight that the strength of a country's dominant commodity in the global supply chain likely reflects in how its exchange rate and commodity price relate to each other. Importantly, this study is among the first to test daily Granger causality between sugar futures and USDBRL and USDZAR, filling a clear gap in soft-commodity currency research.

5.4 Limitations

While the study makes a meaningful contribution to literature on the commodity-currency dynamic, it is not without its limitations that should be acknowledged. Firstly, this study was limited to Brazil and South Africa, two countries with different geographies and political regimes, and although it allowed a comparative lens, it excluded other large raw sugar exporters such as India, Russia, and China. This limits a broader applicability of findings, especially after determining that trade balance weighting of the commodity and global market share influence the dynamic between the raw sugar price and exchange rates.

Secondly, focusing only on two variables, raw sugar and exchange rates, omits the influence of other macroeconomic drivers that influence commodity prices and exchange rates such as interest rates, inflation, and geopolitical events. A multivariate model may also extract meaningful insights to explain price changes. And, lastly, as the study relied on secondary data from a trusted source, the data had gaps which impacts quality, highlighting an interpretative constraint where firm-level hedging decisions are concerned.

5.5 Future research

While this study provided meaningful insights into the short-run causal relationship between nominal exchange rates and raw sugar futures prices, it can be extended in several ways to enhance theoretical understanding and support policymaking, especially in Brazil.

- Assessing the causal linkage between real exchange rates, which are adjusted for inflation differentials, and sugar futures prices to get a more accurate reflection of the dynamics for Brazil and South Africa.
- To inform policymaking, assess how FX and raw sugar futures prices respond to external shocks such as monetary policy interest rate adjustments, trade agreements and tariffs, geopolitical tensions, and weather impact on supply to the broader global market.
- And conducting sugar company-specific analysis on export hedging to link key performance indicators related to financial outcomes and the causality findings of this study.

Through theoretical groundings on the commodity-currency nexus, quantified impact through the causal linkage study between sugar futures prices and nominal exchange rates, as well as suggested future research paths, this study has made a meaningful contribution to literature and provided a platform for future research.

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APPENDIX A: STATA OUTPUT

A1: Optimal lag selection for lnZAR, lnBRL, and lnSFP

```
. varsoc lnzar lnbrl lnsfp

Lag-order selection criteria

   Sample: 05nov2016 thru 31oct2024                     Number of obs = 2,918
```

Lag	LL	LR	df	p	FPE	AIC	HQIC	SBIC
0	3883.71				.000014	-2.65984	-2.65763	-2.65369
1	29163.2	50559	9	0.000	4.2e-13	-19.9803	-19.9714	-19.9557*
2	29191.5	56.66*	9	0.000	4.2e-13*	-19.9935*	-19.978*	-19.9505
3	29196.8	10.483	9	0.313	4.2e-13	-19.9909	-19.9688	-19.9295
4	29200.8	8.0737	9	0.527	4.2e-13	-19.9875	-19.9587	-19.9076

```
   * optimal lag
   Endogenous: lnzar lnbrl lnsfp
    Exogenous: _cons
```

A2: ADF output for lnSFP

```
. dfuller lnsfp, trend regress lags(2)

Augmented Dickey-Fuller test for unit root

Variable: lnsfp                         Number of obs  = 2,919
                                        Number of lags =     2

H0: Random walk with or without drift
```

	Test statistic	Dickey-Fuller critical value 1%	5%	10%
Z(t)	-3.171	-3.960	-3.410	-3.120

MacKinnon approximate *p*-value for Z(t) = 0.0904.

Regression table

D.lnsfp	Coefficient	Std. err.	t	P>|t|	[95% conf. interval]	
lnsfp						
L1.	-.0040427	.001275	-3.17	0.002	-.0065427	-.0015426
LD.	.0907577	.0184946	4.91	0.000	.0544939	.1270216
L2D.	.0251054	.0184842	1.36	0.175	-.011138	.0613489
_trend	1.21e-06	3.89e-07	3.11	0.002	4.45e-07	1.97e-06
_cons	.009531	.0032147	2.96	0.003	.0032276	.0158343

A3: ADF output for lnSFP in first difference

. dfuller dlnsfp, trend regress lags(2)

Augmented Dickey–Fuller test for unit root

Variable: **dlnsfp** Number of obs = **2,918**
Number of lags = **2**

H0: Random walk with or without drift

	Test statistic	Dickey–Fuller critical value 1%	5%	10%
Z(t)	**-29.037**	**-3.960**	**-3.410**	**-3.120**

MacKinnon approximate *p*-value for Z(t) = **0.0000.**

Regression table

D.dlnsfp	Coefficient	Std. err.	t	P>|t|	[95% conf.	interval]
dlnsfp						
L1.	-.8675586	.029878	-29.04	0.000	-.9261428	-.8089743
LD.	-.042361	.0250491	-1.69	0.091	-.0914767	.0067546
L2D.	-.0209799	.0185141	-1.13	0.257	-.057282	.0153221
_trend	3.87e-07	2.90e-07	1.33	0.182	-1.82e-07	9.56e-07
_cons	-.000551	.0004895	-1.13	0.260	-.0015108	.0004088

A4: ADF output for lnZAR

. dfuller lnzar, trend regress lags(2)

Augmented Dickey–Fuller test for unit root

Variable: **lnzar** Number of obs = **2,919**
Number of lags = **2**

H0: Random walk with or without drift

	Test statistic	Dickey–Fuller critical value 1%	5%	10%
Z(t)	**-3.130**	**-3.960**	**-3.410**	**-3.120**

MacKinnon approximate *p*-value for Z(t) = **0.0992.**

Regression table

D.lnzar	Coefficient	Std. err.	t	P>|t|	[95% conf.	interval]
lnzar						
L1.	-.0062896	.0020093	-3.13	0.002	-.0102294	-.0023498
LD.	.0678422	.0185181	3.66	0.000	.0315324	.104152
L2D.	.0053276	.0185184	0.29	0.774	-.0309829	.0416381
_trend	8.45e-07	3.17e-07	2.67	0.008	2.24e-07	1.47e-06
_cons	.0160703	.0051115	3.14	0.002	.0060479	.0260928

A5: ADF output for lnZAR in first difference

```
. dfuller dlnzar, trend regress lags(2)

Augmented Dickey-Fuller test for unit root

Variable: dlnzar                          Number of obs  = 2,918
                                          Number of lags =     2

H0: Random walk with or without drift

                                       Dickey-Fuller
                   Test          ———————— critical value ————————
                statistic           1%           5%          10%
------------------------------------------------------------------
 Z(t)             -30.872       -3.960       -3.410       -3.120
------------------------------------------------------------------
MacKinnon approximate p-value for Z(t) = 0.0000.

Regression table
```

D.dlnzar	Coefficient	Std. err.	t	P>|t|	[95% conf.	interval]
dlnzar						
L1.	-.9465563	.0306605	-30.87	0.000	-1.006675	-.8864378
LD.	.0114556	.0253546	0.45	0.651	-.0382592	.0611703
L2D.	.0149914	.0185157	0.81	0.418	-.0213137	.0512966
_trend	7.68e-10	1.63e-07	0.00	0.996	-3.20e-07	3.21e-07
_cons	.0000827	.0002757	0.30	0.764	-.0004578	.0006233

A6: ADF output for lnBRL

```
. dfuller lnbrl, trend regress lags(2)

Augmented Dickey-Fuller test for unit root

Variable: lnbrl                           Number of obs  = 2,919
                                          Number of lags =     2

H0: Random walk with or without drift

                                       Dickey-Fuller
                   Test          ———————— critical value ————————
                statistic           1%           5%          10%
------------------------------------------------------------------
 Z(t)              -1.967       -3.960       -3.410       -3.120
------------------------------------------------------------------
MacKinnon approximate p-value for Z(t) = 0.6190.

Regression table
```

D.lnbrl	Coefficient	Std. err.	t	P>|t|	[95% conf.	interval]
lnbrl						
L1.	-.0025432	.0012926	-1.97	0.049	-.0050778	-8.65e-06
LD.	.0116368	.0185147	0.63	0.530	-.0246664	.04794
L2D.	.0339893	.0185151	1.84	0.066	-.0023146	.0702933
_trend	4.66e-07	3.06e-07	1.52	0.128	-1.35e-07	1.07e-06
_cons	.003318	.0015821	2.10	0.036	.0002157	.0064202

A7: ADF output for lnBRL in first difference

```
. dfuller dlnbrl, trend regress lags(2)
```

Augmented Dickey–Fuller test for unit root

Variable: **dlnbrl** Number of obs = **2,918**
Number of lags = **2**

H0: Random walk with or without drift

	Test statistic	Dickey–Fuller critical value 1%	5%	10%
Z(t)	-30.801	-3.960	-3.410	-3.120

MacKinnon approximate *p*-value for Z(t) = **0.0000**.

Regression table

D.dlnbrl	Coefficient	Std. err.	t	P>|t|	[95% conf. interval]	
dlnbrl						
L1.	-.9706081	.0315119	-30.80	0.000	-1.032396	-.9088203
LD.	-.0185328	.0260611	-0.71	0.477	-.069633	.0325673
L2D.	.0143352	.0185312	0.77	0.439	-.0220004	.0506708
_trend	-4.56e-08	1.64e-07	-0.28	0.781	-3.67e-07	2.76e-07
_cons	.0002601	.000277	0.94	0.348	-.0002831	.0008032

A8: Johansen cointegration test for lnZAR and lnSFP with constant

```
. vecrank lnzar lnsfp, trend(constant) max
```

Johansen tests for cointegration
Trend: Constant Number of obs = **2,920**
Sample: **03nov2016** thru **31oct2024** Number of lags = **2**

Maximum rank	Params	LL	Eigenvalue	Trace statistic	Critical value 5%
0	6	18674.823	.	10.9114*	15.41
1	9	18679.818	0.00342	0.9215	3.76
2	10	18680.278	0.00032		

Maximum rank	Params	LL	Eigenvalue	Eigenvalue Maximum	Critical value 5%
0	6	18674.823	.	9.9899	14.07
1	9	18679.818	0.00342	0.9215	3.76
2	10	18680.278	0.00032		

* selected rank

A9: Johansen cointegration test for lnBRL and lnSFP with constant

```
. vecrank lnsfp lnbrl, trend(constant) max

Johansen tests for cointegration
Trend: Constant                              Number of obs  = 2,920
Sample: 03nov2016 thru 31oct2024             Number of lags =     2
------------------------------------------------------------------------
                                                               Critical
Maximum                                                 Trace     value
   rank  Params          LL  Eigenvalue   statistic        5%
      0       6   18692.142           .     12.7738*     15.41
      1       9   18697.753     0.00384      1.5524      3.76
      2      10   18698.529     0.00053
------------------------------------------------------------------------
                                                               Critical
Maximum                              ----------Eigenvalue--------   value
   rank  Params          LL                    Maximum         5%
      0       6   18692.142           .        11.2214      14.07
      1       9   18697.753     0.00384         1.5524       3.76
      2      10   18698.529     0.00053
------------------------------------------------------------------------
* selected rank
```

A10: VAR(2) model estimation for lnBRL and lnSFP in first difference

```
. var dlnsfp dlnbrl

Vector autoregression

Sample: 04nov2016 thru 31oct2024                 Number of obs     =      2,919
Log likelihood =   18689.63                      AIC               =  -12.79865
FPE            =   9.48e-09                      HQIC              =  -12.79127
Det(Sigma_ml)  =   9.41e-09                      SBIC              =  -12.77817

Equation           Parms      RMSE     R-sq      chi2     P>chi2
----------------------------------------------------------------
dlnsfp                5     .013166   0.0147   43.46895   0.0000
dlnbrl                5     .007468   0.0014   4.065448   0.3972
----------------------------------------------------------------

------------------------------------------------------------------------------
             | Coefficient  Std. err.      z    P>|z|     [95% conf. interval]
-------------+----------------------------------------------------------------
dlnsfp       |
      dlnsfp |
         L1. |   .0785388    .018718     4.20   0.000     .0418522    .1152254
         L2. |    .019089   .0186522     1.02   0.306    -.0174686    .0556466
             |
      dlnbrl |
         L1. |  -.1127467   .0330068    -3.42   0.001    -.1774389   -.0480545
         L2. |  -.0693194   .0330711    -2.10   0.036    -.1341376   -.0045012
             |
       _cons |   .0000556   .0002437     0.23   0.820     -.000422    .0005331
-------------+----------------------------------------------------------------
dlnbrl       |
      dlnsfp |
         L1. |  -.0025203   .0106164    -0.24   0.812    -.0233281    .0182875
         L2. |  -.0075499   .0105791    -0.71   0.475    -.0282845    .0131847
             |
      dlnbrl |
         L1. |   .0096116   .0187207     0.51   0.608    -.0270804    .0463035
         L2. |   .0303328   .0187572     1.62   0.106    -.0064305    .0670962
             |
       _cons |   .0001908   .0001382     1.38   0.167    -.0000801    .0004616
------------------------------------------------------------------------------
```

A11: VAR(2) model estimation for lnZAR and lnSFP in first difference

```
. var dlnsfp dlnzar

Vector autoregression

Sample: 04nov2016 thru 31oct2024               Number of obs     =      2,919
Log likelihood =   18669.07                    AIC               =  -12.78457
FPE            =   9.61e-09                    HQIC              =  -12.77719
Det(Sigma_ml)  =   9.55e-09                    SBIC              =  -12.76408

Equation           Parms      RMSE     R-sq      chi2     P>chi2
----------------------------------------------------------------
dlnsfp               5     .013196   0.0102   30.21358   0.0000
dlnzar               5     .007437   0.0043   12.48802   0.0141
----------------------------------------------------------------

------------------------------------------------------------------------------
             | Coefficient  Std. err.      z    P>|z|     [95% conf. interval]
-------------+----------------------------------------------------------------
dlnsfp       |
      dlnsfp |
         L1. |   .0885361   .0185593     4.77   0.000     .0521605    .1249117
         L2. |   .0249186   .0185385     1.34   0.179    -.0114161    .0612533
             |
      dlnzar |
         L1. |  -.0562206   .0329317    -1.71   0.088    -.1207654    .0083243
         L2. |     .00683   .0329376     0.21   0.836    -.0577264    .0713864
             |
       _cons |    .000024   .0002441     0.10   0.922    -.0004544    .0005024
-------------+----------------------------------------------------------------
dlnzar       |
      dlnsfp |
         L1. |   .0003257   .0104595     0.03   0.975    -.0201745     .020826
         L2. |  -.0029429   .0104477    -0.28   0.778    -.0234201    .0175343
             |
      dlnzar |
         L1. |   .0649467   .0185593     3.50   0.000     .0285711    .1013223
         L2. |   .0016019   .0185627     0.09   0.931    -.0347803     .037984
             |
       _cons |   .0000857   .0001376     0.62   0.533    -.0001839    .0003553
------------------------------------------------------------------------------
```