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The Lead-Lag Relationship Between International Food Prices, Freight Rates, and Trinidad and Tobago's Food Inflation: A Support Vector Regression Analysis

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Abstract: The objective of this study is to empirically investigate (i) the extent in which shipping costs can cause and predict the food inflation in Trinidad and Tobago (T&T); (ii) the extent in which international food prices can drive food inflation in T&T; and (iii) the impact of the Russia-Ukraine conflict on food prices in T&T. As a fourth sub-objective, this study seeks to provide policy recommendations to address the food price inflation in T&T. A structural model is sought as it can use information about the past prices of the international food prices and shipping rates to forecast T&T's food price inflation. This study used monthly data on T&T retail price index food subcategory, the Food and Agriculture Organization (FAO) Food Price Index (FFPI), and the Freightos Baltic Index over January 2015 to November 2022 period. The Support Vector Regression model was applied and used the FFPI and Freightos Baltic Index as the leading indicators to forecast T&T's food price inflation. This study found that the FAO Food Prices do and the Freightos Baltic Index does have an impact on food prices in T&T. Secondly, based on the FAO index and the Freightos Baltic Index, T&T's food price inflation should be 14.91% lower than its present value. Third, in a Markov Switching regression, the war dummy was only significant in the second regime, statistically suggesting that the Russia-Ukraine conflict only had a short-term effect on T&T's food prices. This contributed to the literature as it introduced a new test to investigate predictive causality. Policy measures to increase the agriculture output and address the food price inflation in T&T include adopting sustainable farming practices such as integrated pest management and the sustainable water management and encouraging aquaponics.

Keywords: international food prices, Freightos Baltic Index, Russia-Ukraine conflict, support vector regression, time series forecasting, artificial neural network causality test

1. Introduction

In November 2022, the retail price index food subcategory in Trinidad and Tobago (T&T) was 145. Since the base year was January 2015, it meant that prices increased by 45% between January 2015 and November 2022. A visual inspection of a longer time series, as seen in Figure 1, reveals that food prices were moderate in T&T over January 2015 to September 2020 period. Post-September 2020, there was an uptick in food prices in T&T.

The change in the slope of the food prices in T&T may be reflective of the change in external macroeconomic conditions. T&T is a small open economy in the Caribbean that is highly vulnerable to external macroeconomic shocks.

On March 11, 2020, the World Health Organization declared the COVID-19 a pandemic (Zanke et al., 2020). T&T, along with the rest of the world, implemented a series of non-pharmaceutical measures to curb the transmission of the virus, which included lockdown measures (Hunte et al., 2020). This caused a decrease in the aggregate supply as well as aggregate demand in countries. In the last quarter of 2020, many countries relaxed their lockdown measures, resulting in a rebound in aggregate demand. However, aggregate supply was not sufficiently elastic to respond, resulting in some inflationary pressures.

Furthermore, shipping and freight disruptions in 2021 also affected food prices. For instance, the Suez Canal experienced accidental blockage in March 2021 (Özkanlisoy & Akkartal, 2022). There was a global shortage of shipping containers throughout 2021 and 2022 (Ruiz et al., 2022). Additionally, in 2021 and 2022 there was port congestion at the Port of Los Angeles and the Port of Long Beach, both of which are major ports in the United States (US) (Kent & Haralambides, 2022).

Apart from the shipping and freight conditions, food prices were increasing due to drought and extreme weather conditions in many major food-producing countries, such as Brazil (drought), the US (wild-fires), China (crop failure), Germany (floods), and the United Kingdom (Dunn et al., 2022). The outbreak of bird flu in the US in 2022 contributed to the rise in the price of poultry and eggs.

Recently, on 24 February 2022, Russia launched an invasion on Ukraine (Kusa, 2022). This action was the culmination of tension from 2021 where Russia was mounting a military presence at Ukraine's border. This action was taken by Russia in response to Ukraine's pursuit of membership in the European Union and North Atlantic Treaty Organization (Götz & Staun, 2022).

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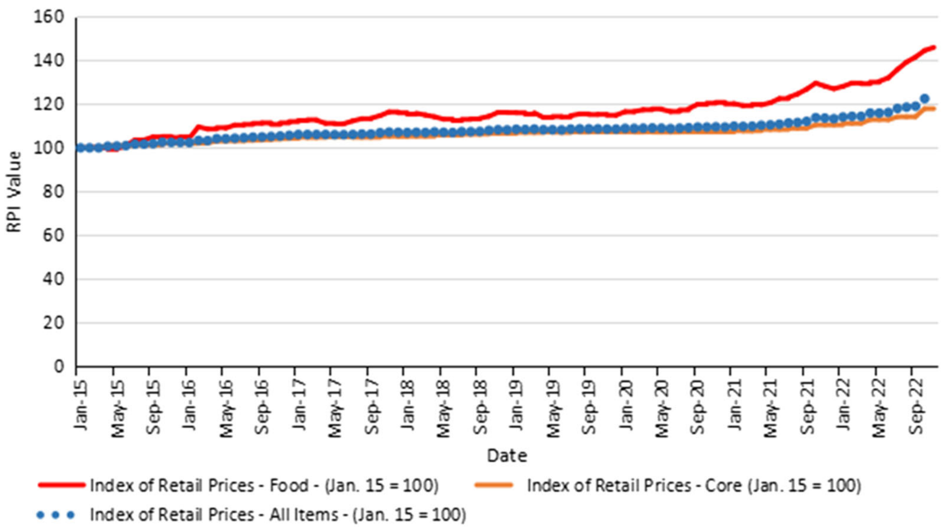
Figure 1
Retail prices index (RPI) in Trinidad and Tobago (2015–2022) (CBTT, 2023)



Russia's actions caused a major disruption to sea trade among the countries in the Black Sea. The Black Sea area was the world's second-largest grain-exporting region in 2021, with 111.2 million tons of cargo; Russia and Ukraine accounted for 30% of global wheat exports, and Ukraine accounted for 16% of global corn exports. There was early speculation that prolonged conflict between Russia and Ukraine would increase shipping rates in the Black Sea and partially disrupt supply chains along Western Europe. While there was initially a blockage in the Black Sea, this was lifted in July 2022 after the United Nations negotiated a maritime "humanitarian corridor" free of naval ships, warplanes, or drones that would allow cargo ships with grain and other food to move out of Ukrainian ports through the Black Sea.

The Russia-Ukraine conflict is being blamed for the rise in food prices in T&T (Ewing-Chow, 2022; Lindo, 2022; Pran, 2022). However, there is a dearth of empirical research to validate this idea.

There are several dated studies on inflation in T&T. For instance, Greenidge and Da Costa (2009) studied the determinants of inflation for Jamaica, Guyana, Barbados, and T&T using annual data from 1970 to 2006.

Serju (2009) investigated the trade-off between growth and inflation stabilization for Jamaica and Trinidad & Tobago. Serju (2009) used a structural vector autoregressive model on quarterly data on GDP and inflation from 1981 to 2008 for the investigation. However, that study's research focus on the sacrifice ratio and the Phillips Curve is different from the focus of this study.

A more relevant paper is Primus et al. (2011) which visually examined the contribution of international and domestic food prices to overall food inflation in T&T from 2005 to 2010. To determine the impact of domestic and international food prices on food inflation, they separated the food price sub-index into two categories: domestically produced items and imported goods. This analysis was limited to a comparison and failed to use any econometric model.

Therefore, there is an absence of empirical research in T&T on food price inflation that considers the current macroeconomic environment.

The objectives of this study are to empirically investigate:

the extent in which shipping costs can cause and predict the food inflation in T&T;

the extent in which international food prices can drive food inflation in T&T; and

if the Russia-Ukraine conflict has a direct impact on food inflation in T&T.

As a fourth sub-objective, this study seeks to provide policy recommendations to address the food price inflation in T&T.

The rest of this study is structured as follows. The second section reviews the data and the methodology for the analysis. The third section presents the results of the analysis and a discussion. The fourth section provides some policy recommendations to address food price inflation in T&T. The fifth section concludes.

2. Research Method

As mentioned in the previous section, there have been other studies on food inflation in T&T. They consider other variables such as the GDP, employment, etc., to help answer their research questions. However, those studies are old and fail to consider the current macroeconomic environment, which includes the Russia-Ukraine conflict and the rise in freight costs.

2.1. Data

Data are collected from the Central Bank of Trinidad and Tobago on the retail price index food subcategory over January 2015 to November 2022 period. This period was selected since January 2015 is the current base year of the price index, and the most recent data point for inflation in T&T at the time of writing was November 2022.

Inflation is typically a lagging variable in economics. Therefore, it can be affected by other variables. The variables considered to impact the inflation include the Food and Agriculture Organization (FAO) Food Price Index, and Freightos Baltic Index (Freight Rate Index).

The Freightos Baltic Index is the benchmark used to measure the spot rates for 40-foot containers on 12 trade lanes. Thus, it can be a good indicator of shipping costs. This was collected from investing website.[1]

The FAO Food Price Index (FFPI) is a measure of the monthly change in international prices of a basket of food commodities,

[1] See https://www.investing.com/indices/baltic-dry-historical-data.

namely meat, dairy, cereals, oils, and sugar. Therefore, it is a good indicator of international food prices. This was collected from the FAO website.[2]

For consistency, data on the FFPI and the Freight Rate Index are collected over January 2015 to November 2022 period. This produced 95 observations per variable, providing a large sample.

2.1.1. Pretesting

Before estimation, pretesting is performed. The data are tested for stationarity using conventional stationary tests (the Augmented Dickey-Fuller (ADF), the Phillips-Perron (PP), and the Kwiatkowski-Phillip-Schmidt-Shin (KPSS)) (Baum, 2000; Dickey & Fuller, 1979; Kwiatkowski et al., 1992; Phillips & Perron, 1988). Descriptive statistics are also applied to determine the normality of the variables.

Prices are known to possess structural breaks (Mensi et al., 2015). Therefore, the Sums of Squares Over Heteroskedasticity (SHOW) test and the Bai-Perron Breakpoint test are applied to determine potential structural breaks.

The SHOW test is a statistical test used to detect structural breaks in time series data. It was developed by Qu and Perron (2007) as an extension of the existing Cumulative Sum (CUSUM) test for structural breaks. The SHOW test is based on the idea that structural breaks can lead to changes in the level of heteroskedasticity in a time series. The SHOW test is based on the idea that structural breaks can lead to changes in the level of heteroskedasticity in a time series, which can affect the accuracy of statistical tests for structural breaks.

The test involves estimating a regression model and then using the residuals to calculate the CUSUM. Under the null hypothesis of no structural break, the test statistic follows a standard F-distribution. If the test statistic is significantly larger than the critical value, then there is evidence of a structural break in the data.

2.1.2. Justification for pretesting

Pretesting for normality and stationarity is an essential step in empirical econometric analysis. Normality testing is used to determine whether the data follow a normal distribution, which is important because many statistical tests rely on the assumption of normality. Stationarity testing is used to determine whether a time series has a stable mean and variance over time, which is important because many statistical models, such as autoregressive models, require stationarity for accurate parameter estimation. If the data are not normal or stationary, then the statistical tests and models used may be invalid or inaccurate, leading to erroneous conclusions.

The importance of testing for structural breaks lies in the potential impact on the results of a study. If structural breaks are present but not accounted for, the estimated parameters may be biased, leading to incorrect conclusions or forecasts. Furthermore, structural breaks can render the ADF, PP, and KPSS tests results as inaccurate, leading to the wrong conclusion of non-stationarity. While models such as the Markov Switching regression can perform piecewise linear regressions that account for structural breaks, they become less parsimonious when they do so. Also, it can result in overfitting, which causes the results to only be relevant within sample and not out of sample.

Granger causality tests whether the past values of one variable help predict another variable after controlling for past values of the other variable. This is an important test as if two variables are correlated, they may appear to have a linear relationship with each other, and a regression may be specified. However, if there is no true causal relationship between the variables, then the result of the regression is essentially a spurious regression.

Granger causality is based on an F-test. The F-test is used to determine whether adding the past values of a potential causal variable to a model improves the model's predictive power. Granger causality tests whether the past values of one variable help predict another variable after controlling for past values of the other variable. If a causal relationship is found, it suggests that changes in one variable lead to changes in the other variable in a predictive way. Therefore, Granger causality is used to infer causality between two variables.

The F-test assumes that the data being tested are normally distributed, have equal variances, and are independent of each other, a phenomenon referred to as independent and identically distributed. If these assumptions are not met, the F-test may not provide accurate results. In addition, spurious outcomes can also arise when the F-test is applied to variables that are not causally related, but are correlated due to the influence of other variables. In such cases, the F-test may suggest a significant relationship between the variables even though the relationship is not causal.

Notable, the violation of the normality assumption provides justification for the use of machine learning models as they do not rely on this assumption.

2.2. Proposed ANN causality test

The causality is tested between the variables. Normally, the Granger causality test is used to determine the causal link between variables. However, this test is based on linear regression models. To overcome this linear constraint, this study proposes a new test for causality using a machine learning framework. More specifically, an artificial neural network (ANN) (Hill et al., 1994) is used to determine the causality between the variables.

Recall the logic from the Granger causality test. If there is a causal relationship from variable X to Y, then adding information about variable X should help accurately predict variable Y. This same principle is applied to the proposed ANN causality test. Moreover, if variable X does not help predict variable Y, then adding variable X in a model to predict variable Y would make the model unnecessarily complex. Furthermore, the training of a neural network on data with no causal relationship may cause overfitting, which may result in the poor performance in out-of-sample forecasts.

The ANN causality test is a simple 3-layer feed forward neural network, with a variable used as the input and another variable used as the output. The input variable is X, or in this case oil prices. The output variable is Y, or in this case silver prices. The model is trained on the training set and validated against the test set. The model is run and used to generate a mean squared error (MSE). The MSE generated from the regression of oil prices on silver prices is called MSE 1.

This MSE 1 is compared to the MSE of a univariate model. In other words, the ANN is applied on variable Y (T&T's retail price index food subcategory) alone. Past Y should be used to forecast future Y. A MSE is generated from this ANN model and is called MSE 2.

Causality will be found if the MSE 1 is less than MSE 2. Furthermore, a ratio can be computed as $MSE\ 1/MSE\ 2$. If $\frac{\text{MSE 1}}{\text{MSE 2}} < 1$, then causality exists from variable X (FFPI) to variable Y (retail price index food subcategory). If $\frac{\text{MSE 1}}{\text{MSE 2}} > 1$ Then, no causality exists from variable X (FFPI) to variable Y (retail price index food subcategory).

The next step of the proposed test involves statistically testing to see if $\frac{\text{MSE 1}}{\text{MSE 2}}$ is statistically significantly less than 1.

The null and alternative hypothesis are as follows:

H0: $MSE\ 1/MSE\ 2 < 1$ (predictive causality exists from variable X to Y).

H1: $MSE\ 1/MSE\ 2 > 1$ (predictive causality does not exist from variable X to Y).

[2]See https://www.fao.org/worldfoodsituation/foodpricesindex/en/.

The null hypothesis is the statistical hypothesis of $MSE\ 1 < MSE\ 2$ is being tested. The alternative hypothesis represents the remaining outcome which is $MSE\ 1 > MSE\ 2$.

If the estimated value of $MSE\ 1/MSE\ 2$ is a long way away from the hypothesized value of less than 1, the null hypothesis is to be rejected.

The test statistic is given by

$$\frac{\left(\mathrm{MSE1}/\mathrm{MSE2}\right)}{\mathrm{SE}} \tag{1}$$

where SE is the standard error or $\frac{\sigma_{xy}}{\sqrt{n}}$

σ_{xy} is the covariance to the variables X and Y
n is the number of observations
The critical region is given by

$$\frac{1}{\mathrm{SE}} \tag{2}$$

The decision rule for this right-tailed test is as follows

If the test statistic is less than the critical region, then do not reject the null hypothesis.

If the test statistic is greater than the critical region, then reject the null hypothesis in favor of the alternative hypothesis.

The non-rejection of the null hypothesis suggests that $MSE\ 1 < MSE\ 2$, and there is predictive causality from variable X to Y. The rejection of the null hypothesis suggests that the $MSE\ 1 > MSE\ 2$, and there is no predictive causality from X to Y.

Note, this is a right-tailed test as the null hypothesis is rejected at values greater than the critical region.

2.3. Estimation-SVR

The main methodology used for estimation is based on the Support Vector Regression (SVR).

The Support Vector Machine (SVM) is a supervised learning model that analyses observed data and sorts the data into different classifications (Shen et al., 2012). The basic idea behind the SVM is to sort the data into 1 out of 2 different classifications while avoiding the overfitting problem that is common with machine learning models (Vapnik, 1998).[3] In the case of classification, the support vectors use a hyperplane to separate the data into categories. A modification can be performed; the support vectors are used as points to minimize the error in the regression. This gives rise to the SVR (Ojemakinde, 2006).

The idea behind SVR is to define an approximation of the regression function within a margin utilizing a set of support vectors. Like traditional regression models, the regression can be univariate or multivariate. Regardless of if the regression is univariate or multivariate, the SVR specifies a function to model or extract the underlying shape of the input-output relationship to be estimated.

Like the ANN model, the data used to perform the SVR are divided into subsamples for training and testing. The data are trained with the SVR, and the results are compared to the testing data. The SVR model seeks to minimize the generalization error, which is the misclassification error arising from data falling in the soft margin.[4] In contrast, the ANN model seeks to minimize the prediction error (the difference in the results between the training and the testing data) (Claveria et al., 2015).

[3]Overfitting is a problem in machine learning models where the model produces good results after it has been trained on specific data. However, the model performs poorly in estimation and forecasting on new untrained data. Overfitting can be addressed by cross-validation, where the data are divided into different samples for training, and the results of the training data are compared to the data that was not trained (the testing data).

[4]The accuracy of the SVR should increase the further away the point estimate is away from the support vectors and the hyperplane.

2.4. Impact of the Russia-Ukraine conflict

There are several approaches that can be used to determine if the Russia-Ukraine conflict has an impact on the price level in T&T.

One approach is to specify a regression with a dummy variable.

The equation to capture the effect of food prices on inflation in T&T is specified as follows

$$\mathrm{FRPI} = \beta_0 + \beta_1 \mathrm{FRPI}_{t-1} + \beta_2 \mathrm{FAO}_t + \beta_3 \mathrm{FBI}_t + \mathrm{D}_t + \varepsilon_t \tag{3}$$

where FRPI is the retail price index food subcategory, FRPI_{t-1} is an autoregressive term, FAO_t is the *FFPI*, FBI_t is the Freightos Baltic Index, $\beta_{0..3}$ is the estimated marginal effects, D_t is a dummy variable to capture the effect of the Russia-Ukraine conflict, and ε_t is the error term.

The dummy variable assumes the value of 0 for the months before the conflict and a value of 1 for the months of the conflict. The coefficient of the dummy variable is tested for statistical significance. If the variable is found to be statistically insignificant from 0, then it suggests that the Russia-Ukraine conflict has no impact on the food price level in T&T.

Note, this dummy variable approach is used rather than a machine learning model as the objective was only to test if the Russia-Ukraine conflict is significant. Additionally, there is a need to generate a coefficient and test for statistical significance.

A Markov Switching Regression is used to model this relationship (Uzoma & Florence, 2016). All non-stationary variables are differenced to become stationary and included in the regression. All the variables are allowed to switch regimes. The number of regimes is determined in the Bai-Perron Breakpoint test (Phoong et al., 2020).

3. Results and Discussion

3.1. Pretesting results

The descriptive statistics for the variables are presented in Table 1. The FFPI is labeled FAO, Freightos Baltic Index is labeled FBI, and the retail price index food subcategory is labeled FRPI.

Table 1
Descriptive statistics

	FRPI	FAO	FBI
Mean	116.2316	104.9084	1384.874
Median	115.0000	96.80000	1227.000
Maximum	145.9000	159.7000	5167.000
Minimum	99.30000	84.90000	317.0000
Std. Dev.	9.444465	18.48655	856.4035
Skewness	0.861490	1.480867	1.741493
Kurtosis	4.227402	4.075302	6.938451
Jarque-Bera	17.71423	39.29889	109.4186
Probability	0.000142	0.000000	0.000000
Sum	11042.00	9966.300	131563.0
Sum Sq. Dev.	8384.605	32124.73	68942128
Observations	95	95	95

The null hypothesis of the Jarque-Bera test is the series that is normally distributed. Since the probability of the Jarque-Bera test statistic is less than the 1%, 5%, and 10% critical values for each time series, the null of normality can be rejected. This suggests that the FFPI, Freightos Baltic Index, and the retail price index food subcategory are not normally distributed, and models based on the assumption of normality may not be appropriate for modeling.

The stationarity test results are displayed in Table 2. The results of the ADF and PP test suggest the non-rejection of the null hypothesis of 1-unit root when the series are at level. However, the null hypothesis of 1-unit root is rejected when the series is at 1st difference. This suggests that the time series are non-stationary with 1-unit root.

In the KPSS, the null hypothesis is stationarity. However, this null hypothesis was rejected as the KPSS test statistic fell in the rejection zone at level for all the variables. However, the KPSS test statistic fell in the non-rejection zone at 1st difference, at the 5% and 1% significance levels for the retail price index food subcategory. This non-rejection at the 1% and 5% levels suggested that the time series are stationary in the weak sense after first differencing.

Table 2
Stationarity results

	FRPI	FAO	FBI
ADF (level)	0.9999	0.8381	0.1207
ADF (1st diff)	0.0000	0.0000	0.0000
PP (level)	0.9999	0.8871	0.0875
PP (1st diff)	0.0000	0.0000	0.0000
KPSS (level)	1.147450	0.826602	0.7463
KPSS (1st diff)	0.425614	0.2045	0.0442
KPSS critical values	1% level	0.739	
	5% level	0.463	
	10% level	0.347	
BP (level)	0.99	0.2401	0.3219
BP (1st diff)	0.01	0.01	0.01

The Bai-Perron stationarity with structural breaks test is also applied. The results in Table 2 suggest that all the time series are non-stationary with a structural break at level. However, at 1st difference they are stationary with a structural break.

To confirm the existence of the structural break, a linear regression is specified where the retail price index food subcategory is a function of a constant, the FAO food prices, the Freightos Baltic Index. The results are presented in Table 3a. The results of the structural break test reveal the existence of 3 structural breaks. This is evidenced by the F-statistic being less than the critical value at the null hypothesis of there being 3 structural breaks. In this right-tailed test, the null hypothesis was not rejected. This result of a structural break also suggests that a linear model is not appropriate for modeling the food prices. Moreover, this also implies that the marginal effects stipulated by the beta coefficients from linear regression models may be misleading.

Table 3a
Bai-Perron breakpoint test results

Sequential F-statistic determined breaks:			3
Break Test	F-statistic	Scaled F-statistic	Critical Value**
0 vs. 1*	28.10090	84.30271	13.98
1 vs. 2*	30.05609	90.16827	15.72
2 vs. 3*	12.95548	38.86645	16.83
3 vs. 4	3.581992	10.74598	17.61

Table 3b
SHOW test results

	$CUSUM_T$ $e = 0.05$
$T = 100$	0.00699
$T = 200$	0.00368
$T = 500$	0.00165

A linear regression was specified according to Equation (3). The null hypothesis of the SHOW test is that there are no structural breaks in the time series. The probability of the test statistic was less than 5% significant level at sample size (T) of 100. This suggests the rejection of the null in favor of the alternative of the presence of structural breaks. See Table 3b.

Next, the causal relationship is tested between the variables with the Granger causality test. The results are displayed in Table 4.

Table 4
Pairwise Granger causality results

Null Hypothesis:	Obs	F-Statistic	Prob.
FBI does not Granger cause FRPI	93	0.77304	0.4647
FRPI does not Granger cause FBI		0.28771	0.7507
FAO does not Granger cause FRPI	93	5.86684	0.0041
FRPI does not Granger cause FAO		1.85047	0.1632
FAO does not Granger cause FBI	93	3.21844	0.0448
FBI does not Granger cause FAO		1.38584	0.2555

The null hypothesis of the Granger causality test is that the variable X (independent variable) does not Granger cause the variable Y (dependent variable). As can be seen in Table 4, when the food RPI is the dependent variable, Granger causality was not found from the freight index to the food RPI. This is evident by the probability of the Granger causality test statistic being above the 1%, 5%, and 10% significance levels, indicating the non-rejection of the null hypothesis of no Granger causality.

Given this approach, no Granger causality was found from the food RPI to the freight index. No Granger causality was found from the food RPI to the FFPI. No Granger causality was found from the freight index to the FFPI. This was evident by the probability of the Granger causality test statistic being greater than the 1%, 5%, and 10% significance levels, indicating the non-rejection of the null hypothesis of no-Granger causality.

However, Granger causality was found from the FFPI to the freight index. Granger causality was found from the FAO index to the food RPI. Given that the Granger causality test is only valid in linear models, the proposed ANN causality test is applied as a non-linear test.

3.1.1. Proposed causality test

As can be seen from Table 5, the MSE 1 is less than MSE 2 for the FAO food index and the Food RPI. The MSE 1 was generated from the regression where the FAO index is used to predict the Food RPI. The MSE from the ANN is used as MSE 1. The MSE 2 was generated from the regression where past Food RPI was used to forecast future silver prices. The MSE produced from this univariate regression is called MSE 2.

The finding that MSE 1 was less than MSE 2 suggests that an ANN from FAO index to Food RPI has greater predictive accuracy than an ANN based on the Food RPI alone. This is interpreted as evidence of causality from the FAO index to Food RPI.

Table 5
Proposed ANN causality test

	FAO to FRPI	FBI to FRPI
MSE 1	22.709	54.3429
MSE 2	85.2356	114.25
MSE 1/MSE 2	0.266422	0.475654428
Cov (xy)	141.6323	4464.415
$\sqrt{n}$	9.746794	9.746794
SE	14.53117	458.0393
Critical region (1/*SE*)	0.068818	0.002183
Test stat	0.018334	0.00104

This test is enhanced by performing a statistical significance test. As previously mentioned, this is a right-tailed test as the null hypothesis is rejected at values greater than the critical region. The test statistic for the FAO index to Food RPI of 0.018334 was less than the critical region of 0.068818. This suggests the non-rejection of the null hypothesis that MSE 1/MSE $2 < 1$. This statically suggests that predictive causality exists from the FAO index to Food RPI.

This ANN causality test is also applied between the Food RPI and the Freightos Baltic Index. Causality was found from the Freightos Baltic Index to the Food RPI. These results answer the first two research questions.

The ANN causality test results also suggest that a traditional linear model may not be appropriate to model the relationship between these variables. This provides further justification for machine learning models such as the SVR. This is displayed in the next section.

3.2. SVR results for food RPI

The results of the SVR are displayed in Figures 2, 3, and 4.

The response plot for the Food RPI shows a good response. The prediction performance and the fit of the regression all suggest a good fit of the SVR model with low within-sample errors.

As can be seen from Table 6, the SVR provided an out-of-sample forecast that was 14.91% lower than the actual data. This finding is significant because it suggests that based on the FFPI

Figure 2
Response plot (Food RPI)

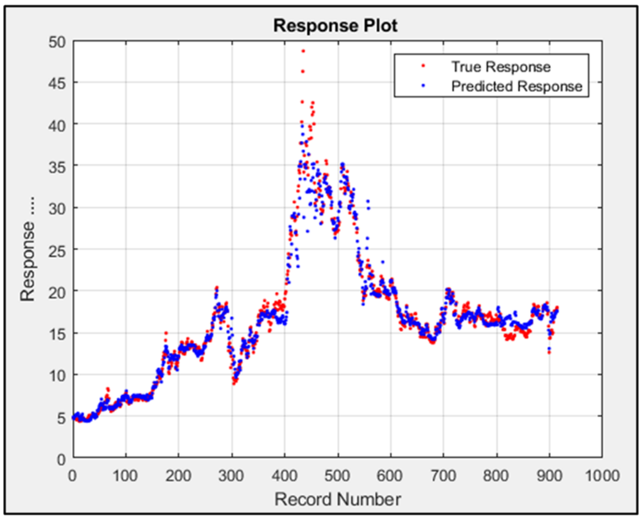


Figure 3
Predictions performance (Food RPI)

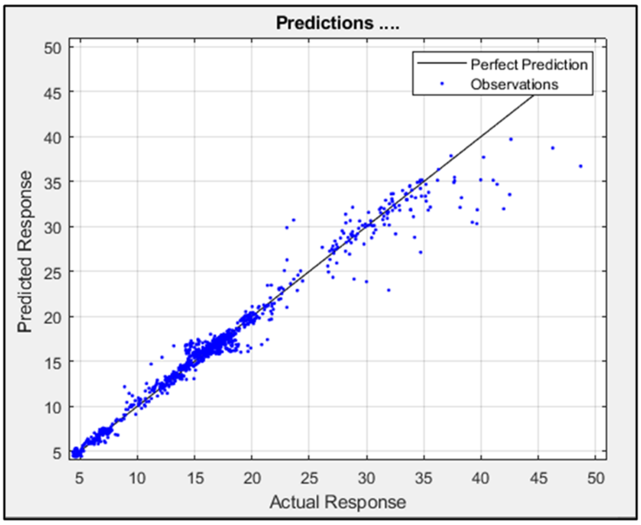


Figure 4
Fit of the regression (Food RPI)

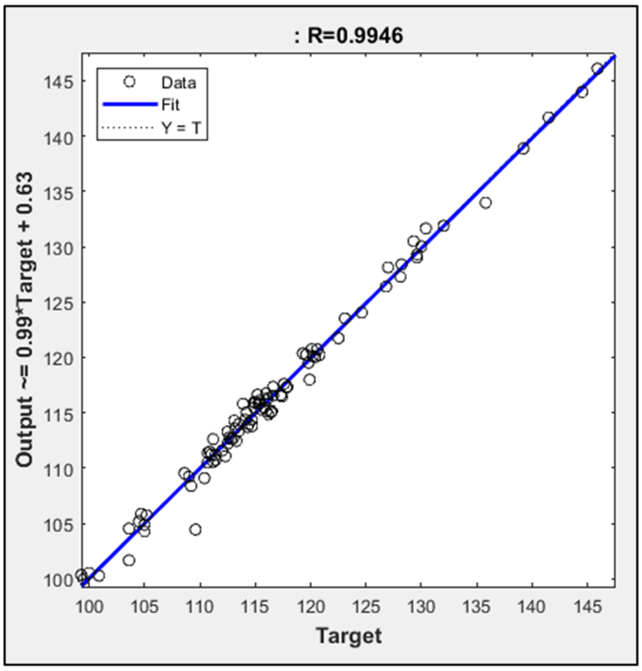


Table 6
SVR out-of-sample forecast

Variable	Silver
Forecast (7/12/2020)	120.8867
Actual data (7/12/2020)	135.8
Actual error	14.9133% lower

Note: The values in this table are an index which already shows a percentage. 120 represents 20% higher than the base year. Therefore, if the difference between the indices is 14.91, then it is a 14.91% difference relative to the base year.

and the Freights Baltic Index, then T&T's Food RPI should be lower than its current value.

3.3. Results showing the impact of the Russia-Ukraine conflict

The results of the Markov Switching Regression are displayed in Table 7. The dummy variable for the Russia-Ukraine conflict was labeled "war."

Table 7
Markov switching regression

Variable	Coefficient	Std. Error	z-Statistic	Prob.
Regime 1				
C	3.423406	0.705126	4.855027	0.0000
DFAO	1.503413	0.549069	2.738111	0.0062
DFBI	0.000583	0.003802	0.153238	0.8782
WAR	3.569682	3.856861	0.925541	0.3547
Regime 2				
C	0.241364	0.196447	1.228645	0.2192
DFAO	−0.059120	0.068962	−0.857295	0.3913
DFBI	−0.001199	0.000326	−3.675107	0.0002
WAR	1.731841	0.859806	2.014224	0.0440
Regime 3				
C	0.233245	0.160049	1.457332	0.1450
DFAO	−0.039016	0.091998	−0.424098	0.6715
DFBI	0.001743	0.000414	4.208376	0.0000
WAR	0.406196	0.565192	0.718688	0.4723
Common				
LOG(SIGMA)	−0.368214	0.101074	−3.643013	0.0003
Probabilities Parameters				
P1-C	−3.070051	0.976723	−3.143215	0.0017
P2-C	−0.089338	0.503440	−0.177455	0.8592

As can be seen in the Markov Switching Regression with 3 regimes, the "war" dummy variable was statistically insignificant from 0 in the first regime. This was evidenced by the probability of its test statistic being greater than 10%, suggesting the non-rejection of the null hypothesis that the beta coefficient is statistically insignificant from 0 at the 1%, 5%, and 10% significance levels.

Using this approach, it can be seen that the "war" dummy variable was statistically significant during the second regime and statistically insignificant at the third regime. This result suggests that the Russia-Ukraine war did not have an effect on T&T's food prices before February 2022, which is expected. The war did have an effect on T&T's food prices in regime 2, which was immediately after the start of the war. However, the effect was short-lived as there was no effect in the third regime. This statistically suggests that the Russia-Ukraine war only had a temporary effect on increasing food prices in T&T.

4. Low-Carbon Economy Recommendations

As can be seen from the empirical analysis section, based on the external factors, T&T's food price inflation should be lower than its present value. This suggests that the local food price inflation is being partially driven by internal factors, despite the food being imported from foreign sources. In this regard, policy measures to address the local demand and supply factors can be used to help mitigate T&T's food price inflation.

The Government of the Republic of Trinidad and Tobago (GORTT) is committed to boosting agriculture output in the country. To this end, the Government is currently implementing a TT$500 million Agriculture Stimulus Package. There is scope for the government to use the Agriculture Stimulus Package to encourage the widespread adoption of sustainable farming practices, which can simultaneously boost agriculture output to reduce food price inflation while maintaining a low-carbon economy. This is logical since sustainable farming practices will balance the needs of increasing agricultural output with the protection and conservation of natural resources, reducing greenhouse gas emissions, and improving the well-being of farmers and rural communities.

Some of the sustainable farming practices that could be adopted include integrated pest management (IPM) and the sustainable water management.

4.1. Integrated Pest Management

IPM is an approach to pest management that involves using a combination of techniques to control pests in a sustainable manner. IPM involves the use of various techniques, including biological control, cultural control, and physical control methods.

Biological control involves the use of natural predators, parasites, and pathogens to control pest populations. This technique can be implemented in a sustainable manner by introducing beneficial organisms to the environment to control pests. Biological control can be sustainable because it does not involve the use of synthetic pesticides, which can be harmful to the environment and human health. Additionally, it can be cost-effective in the long run because natural enemies can establish themselves in the environment and continue to control pests without the need for further intervention.

Cultural control involves the manipulation of the environment to reduce the impact of pests on crops. This technique can be implemented in a sustainable manner by using practices that enhance plant health and reduce the susceptibility of crops to pests. Cultural control can be implemented by rotating crops to reduce the buildup of pest populations, planting pest-resistant varieties, and improving soil health through the use of cover crops and compost.

Physical control methods involve the use of physical barriers or traps to control pest populations. This technique can be implemented in a sustainable manner by using non-toxic materials that do not harm the environment or beneficial organisms. Physical control methods can be implemented by using sticky traps to control insect populations and netting to protect crops from birds and other pests.

The implementation of IPM techniques requires the collaboration of several stakeholders, including the farmers, the government, and local research agencies. To implement the appropriate IPM measures in T&T, the following steps can be taken:

The government, through the Ministry of Agriculture, can conduct an assessment of the pests affecting the crops in T&T. This will identify the most pressing issues and the appropriate IPM measures to address them.

Identify the farmers who will be participating in the IPM program. This can be done through collaboration with local agricultural associations, farmers' markets, regional corporations, and the National Agricultural Marketing and Development Corporation.

Train the participating farmers in IPM practices. This training can be conducted in collaboration with the government agencies.

Provide financial support for the IPM program through the Agriculture stimulus program. The funding should be allocated to cover the costs of training, supplies, and technical assistance.

Monitor the effectiveness of the IPM program regularly to evaluate the impact of the measures and make necessary adjustments.

4.2. Sustainable water management

Sustainable water management is a critical aspect of agriculture that can contribute to increasing productivity. Some sustainable water management practices that can be adopted include improving irrigation efficiency, cultivating water-efficient crops, and reducing fertilizer use.

Irrigation is a crucial aspect of agriculture that can significantly affect productivity. Improving irrigation efficiency can help to reduce water waste. Indirectly, it contributes to the low-carbon economy as it minimizes the need for energy-intensive irrigation systems. This can be achieved through practices such as drip irrigation, which delivers water directly to plant roots and minimizes water loss through evaporation or runoff. Other practices, such as furrow or flood irrigation, can also be made more efficient through the use of smart irrigation systems that use weather data and soil moisture sensors to optimize water use.

Water-efficient crops are those that require less water to produce a given yield, which can help to reduce water use and GHG emissions while increasing agricultural productivity.

Water management practices such as soil conservation and cover crops can improve soil health, leading to reduced need for chemical fertilizers. Chemical fertilizers are energy-intensive to produce and are a significant source of GHG emissions. Using organic fertilizers instead can also reduce the need for fossil fuel-derived fertilizers, further reducing GHG emissions.

The GORTT can encourage sustainable water management by taking the following steps.

Provide financial incentives: The government can offer financial incentives to farmers who adopt sustainable water management practices, such as subsidies for drip irrigation systems or water harvesting infrastructure. These incentives can help to offset the initial costs of adopting these practices, making them more accessible to farmers.

Offer technical assistance: The government can provide technical assistance to farmers to help them adopt sustainable water management practices. This can include training programs on water-efficient irrigation techniques, assistance with the design and construction of water harvesting infrastructure, and support for the adoption of cover crops or reduced tillage practices to reduce soil erosion.

Establish guidelines and best practices: The government can establish guidelines for farmers to adopt sustainable water management practices. For example, the government through the Ministry of Agriculture can provide booklets which advise farmers how to reduce water usage, use water-efficient irrigation systems, or implement water harvesting.

4.3. Other sustainable agriculture practices

The government can also encourage the implementation of additional sustainable agriculture practices. They include the following:

Crop rotation: Crop rotation involves growing different crops in a specific order in the same field over time. This practice helps to improve soil health by reducing soil erosion, controlling pests and diseases, and enhancing soil fertility.

Conservation tillage: Conservation tillage is a practice that minimizes soil disturbance during planting and harvesting, preserving the structure and composition of the soil. This practice helps to reduce soil erosion, improve soil quality, and conserve moisture.

Cover cropping: Cover cropping involves planting crops that are not harvested but instead left in the field to cover and protect the soil. Cover crops help to reduce soil erosion, improve soil fertility, and prevent weed growth.

Agroforestry: Agroforestry involves the integration of trees, shrubs, and other perennial plants into farming systems. This practice helps to improve soil fertility, reduce soil erosion, and provide habitat for wildlife.

Soil health management: Soil health management practices include the use of organic fertilizers, composting, and reduced tillage to improve soil fertility, reduce soil erosion, and conserve moisture.

4.4. Technology in farming-aquaponics

Aquaponics is an innovative and sustainable agricultural method that combines hydroponics, which is the cultivation of plants in nutrient-rich water, with aquaculture, which is the farming of aquatic animals such as fish. The system operates as a closed-loop ecosystem where fish waste is converted into nutrients for the plants, which in turn filters the water for the fish. This symbiotic relationship between plants and fish creates a natural, self-sustaining environment that can significantly increase agricultural output in T&T.

One of the key advantages of aquaponics is its efficiency in utilizing resources. In traditional agriculture, plants require large amounts of water and nutrients, and excess nutrients can leach into the environment, causing pollution. Aquaponics eliminates these issues by recycling water and nutrients in a closed-loop system. The fish provide the nutrients for the plants, thus eliminating the need for fertilizers. Furthermore, aquaponics uses up to 90% less water than traditional farming techniques as the water is continuously recycled within the system.

Aquaponics is also highly adaptable and can be implemented in a variety of settings. It can be used in urban areas where space is limited. This makes it a great option for urban agriculture in T&T, where population density is high and there is high competition for land use. Additionally, aquaponics can be used to grow a variety of crops, leafy vegetables, and herbs, as well as fish such as tilapia, catfish, and trout. This versatility makes it an attractive option for aspiring households as well as entrepreneurs in T&T. It provides the dual benefit of a source of food and an avenue to generate income.

The GORTT can encourage the adoption of technology in farming by creating a grant specifically for aquaponics farming. A well-structured grant program can help to incentivize farmers to invest in aquaponics farming and can provide the financial support needed to cover the initial start-up costs.

Eligibility Criteria: The first step in structuring a grant program for aquaponics farming in T&T is to establish the eligibility criteria. The eligibility criteria should be designed to target farmers who are interested in adopting aquaponics but may not have the resources to do so on their own. This could include small-scale farmers, young farmers, and farmers in underserved communities.

Funding Amounts: The grant program should offer funding amounts that are sufficient to cover the costs of setting up an aquaponics system. The funding amounts should be designed to be attractive enough to encourage farmers to participate.

Matching Requirements: The grant program could require farmers to match a portion of the funds provided by the grant. This would help to ensure that farmers are invested in the success of their aquaponics operations and would also help to stretch the grant funds further. The matching requirement could be structured in a way that is flexible and accessible to all farmers, such as allowing farmers to contribute their labor or materials as part of the matching requirement.

Sustainability Requirements: The grant program could require farmers to adopt sustainable and environmentally friendly practices in their aquaponics operations, such as using renewable energy sources or implementing water conservation measures. This would help to promote sustainable agriculture practices and mitigate against potential negative externalities from aquaponics farming.

Reporting Requirements: The grant program could require farmers to submit regular reports on the progress of their aquaponics operations, including information on yields, water usage, and energy usage. This would help to ensure that the grant funds are being used effectively and would also help to identify best practices that could be shared with other farmers.

Training and Education: In addition to providing financial assistance, the GORTT could also use the agriculture stimulus program to provide training and education to farmers who are interested in adopting aquaponics. This training could cover a wide range of topics, including the design and construction of aquaponics systems, the selection and care of fish and plants, and best practices for maintaining water quality and preventing disease.

5. Conclusion

This study modeled the relationship between the FFPI, the Freightos Baltic Index, and T&T's Food Retail Price Index. Monthly data were collected from January 2015 to November 2022.

First, this study found that all of the prices were not normally distributed, non-stationary, and experienced structural breaks. The evidence of non-normality and the presence of structural breaks suggest that linear regression models are not appropriate for modeling the prices.

The traditional linear Granger causality test found:

No Granger causality from the freight index to the food RPI.
No Granger causality from the food RPI to the freight index.
No Granger causality from the food RPI to the FFPI.
No Granger causality from the freight index to the FFPI.
Granger causality from the FFPI to the freight index.
Granger causality from the FAO index to the food RPI.

Given that the Granger causality test is only valid in linear models, the proposed ANN causality test was applied as a non-linear predictive causality test.

The originality of this work is based on the fact that to date there is no evidence in the reviewed literature of studies that the SVR, a machine learning model, to regress the relationship between T&T's food prices, and international food prices, and international freight rates. Additionally, no study to date has considered these factors as well as the recent Russia-Ukraine war.

From a methodology perspective, this study also makes a contribution as it introduced a new predictive causality test based on an ANN. This is a useful contribution as the test applies a non-linear and machine learning model, which is appropriate for non-linear time series.

Notably, while T&T's food RPI was used as the main dependent variable, this study can be replicated for other countries using their food inflation index.

The findings of this study have implications for the business community, imports, exporters, retail stores, consumers, and policy makers. It explains that the external macroeconomic developments, namely international food prices and international freight rates, have an effect on the food inflation in T&T. However, these factors are not solely responsible for T&T's food inflation.

Second, the Russia-Ukraine war had only a temporary effect on T&T's food prices. Therefore, commentaries that blame the Russia-Ukraine war for T&T's food inflation seem to be political.

Third, T&T's food inflation can be tackled by addressing local factors, as the international developments are not the sole cause of the domestic food inflation.

The GORTT is presently in the process of implementing a TT $500 million Agriculture Stimulus Package. The Agriculture Stimulus Package can help increase food output in T&T to address inflation, while maintaining a low-carbon economy. This can be achieved through the promotion of sustainable agriculture practices. The stimulus package can provide incentives and support for farmers to adopt sustainable agriculture practices that reduce the use of chemical fertilizers and pesticides, promote soil health, and conserve water. This will not only reduce the carbon footprint of agriculture but also lead to increased yields and improved soil fertility over the long term.

Moreover, the adoption of technology in agriculture such as aquaponics can help improve water efficiency as less water is used for crop cultivation, increase crop yields as more crops can be cultivated in smaller areas, and reduce chemical use, as the nitrates from the fish waste will be used to feed the pants rather than fertilizer. Indeed, aquaponics is a sustainable farming technique that can contribute to food security and help address food price inflation, while maintaining a low-carbon economy.

Conflicts of Interest

The author declares that he has no conflicts of interest to this work.

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