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Climate Change and Inflation: The Role of Climate Variables in Inflation Modelling

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ABSTRACT

Climate-change has the potential to impact an economy's inflation dynamics. Within the last decade, climate change impacts have had related spillovers on inflation, possibly affecting the ability of monetary policy to achieve its objectives. However, climate-related variables are still generally absent from central banks' policy analysis and forecasting frameworks. This paper investigates the impact of climate change on inflation and evaluate whether there is predictive gain from its inclusion in inflation forecasting. Utilising Vector Error Correction Modelling (VECM) over the first quarter 1991 to the fourth quarter 2022 the study finds that climate change has added to the price momentum over the years. Temperature and precipitation along with hot days, wet days and natural disasters have an increasing effect on food, core and headline inflation in the short-run. Meanwhile, in the long-run all variables with the exception of natural disasters increase food, core and headline inflation. Scenario analysis based on assumptions of increased warming suggests that climate change can influence the rate at which prices are rising and impact climate-sensitive sectors. The study supports that accounting for climate in inflation forecasting can improve a central bank's policy analysis and forecasting frameworks.

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Climate Change and Inflation: The Role of Climate Variables in Inflation Modelling

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Introduction

In April 2023, the mean temperature of the ocean's surface reached 21.1°C surpassing the previously established global record of 21°C – set in 2016 (Quade 2023). Although the increase seems minimal, there is growing evidence that the rise in global surface temperatures over the years has increased the intensity, duration and frequency of natural disasters (Lindsey and Dahlman 2022).

Because of the risks associated with global warming financial regulators, including central banks have stepped up efforts to monitor and curb the impact of climate change. For instance, in 2022 the United States' (US) Securities and Exchange Commission (SEC) proposed a rule change that would require listed companies to disclose their climate risks (SEC 2022). Meanwhile, the United Nations developed a comprehensive good practice guide for financial institutions seeking to understand and develop climate stress testing (UNEP 2021).

Central banks have also been paying attention to the price stability implications of global warming (Kotz, Kuik, et al. 2023). For example, the European Central Bank (ECB) has a climate action plan following the conclusion of its review of monetary policy strategy (Drudi, et al. 2021), and the Network for Greening the Financial System (NGFS) continues to play a significant role in helping central banks strengthen their macro-financial frameworks to incorporate climate change (Network for Greening the Financial System 2020). There are three main channels through which climate change can affect central banks' primary mandate of price stability. Firstly, the physical channel, which entails a price effect, notably food price increases emanating from the occurrence of a climatic event, such as windstorms, earthquakes, floods, extreme precipitation and heat. Secondly, with the transition to net zero carbon emissions, carbon prices can increase affecting consumer prices both directly and indirectly. Directly, through higher electricity rates and fuel prices, and indirectly through increased costs of production for firms across different sectors. Thirdly, higher temperatures and increasing adverse weather events can dampen economic activity and reduce labour productivity. This can impact the long-term productive capacity of the economy, which have implications for monetary policy (Lagarde 2021).

In the literature, very few studies have looked at the effect of climate change on prices[1]. Of the studies surveyed, there is a growing consensus among researchers that there is increased inflation, inflation persistence, and inflation volatility associated with climate shocks, policies and spillovers (Mann 2023). Domestically, climate change does not pose an immediate systemic threat to financial stability (CBTT 2022). However, the 'Vulnerability and Capacity Assessment Report' of 2019 and the 'Coastal Zone Vulnerability and Adaptation Assessment Report' of 2020 found evidence of: (i) rising temperatures; (ii) increased coastal erosion; and (iii) harsher dry and wet seasons (GORTT 2021). This increases the likelihood of dangerous climatic events, which carry implications for financial stability and monetary policy. In Trinidad and Tobago, with 80.0 per cent of socio-economic activities and 70.0 per cent of the population located on coastal areas, the threat to human social and economic survival is great.

[1] See Heinen et al. 2018, Parker 2018 and Faccia et al. 2021.

Given the limited research in the area, particularly for the Caribbean region, the paper provides an empirical basis for central banks to consider climate change in executing its price stability mandate. The Caribbean region is prone to climatic shocks[2] due to its geographic location (located on the hurricane belt[3]) which arguably offers an interesting context within which to study the impact of climate change on prices. Additionally, countries in the Caribbean region rely on imports for a large part of its consumption goods, which makes us sensitive to external supply shocks which impact prices.

From the results of the study, there is evidence that climate change has added to the inflation dynamics over the years. Food, core and headline inflation were found to respond positively to climatic shocks in the short-run and long-run. More specifically, higher temperature, precipitation and natural disasters increase food, core and headline inflation in the short-run. Meanwhile, higher temperature and precipitation increases food, core and headline inflation in the long-run. The study suggests that accounting for climate in inflation forecasting can improve model predictions, which can support effective monetary policy decision-making. Additionally, a scenario analysis based on an assumption of increased warming suggests climate change can influence the rate at which prices are rising and impact climate-sensitive sectors. The rest of the paper is organised as follows; Section 2 examines empirical research on climate change and its impact on inflation. Section 3 provides some stylised facts on domestic weather conditions and its interplay with inflation. Section 4 develops an empirical framework for examining the impact of climate on inflation. Section 5 discusses the results of the empirical framework. Section 6 evaluates whether there is predictive gain in incorporating climate variables into the inflation forecasting framework. Section 7 provides a scenario analysis to show how increased warming can impact inflation volatility, economic activity and weather variability. The paper concludes in section 8 with some policy recommendations.

Literature Review

The literature on climate change and inflation is expanding. Very few studies examined the effect of the big four natural hazards (Tropical Cyclones, Floods, Droughts and Wildfires) on prices, while more recent studies look at the impact of extreme temperatures on various measures of prices: consumer prices (including the food and non-food components), producer prices, and the GDP deflator. Across the various studies surveyed, four general areas of empirical modelling approaches stand out, namely; (i) Vector Autoregression analysis, (ii) local projections (LP) (iii) survey analysis and (iv) Dynamic Stochastic General Equilibrium (DSGE) modelling.

Vector Autoregression (VAR), which is widely used in time series analysis to examine the dynamic relationships among variables (Kotzé 2019), relates current observations of a variable with past observations of itself and past observations of other variables in the system (Eric 2021). Due to these properties, VARs provide a flexible macroeconomic framework that allow researchers to analyse the impact of time-varying weather-related events against time-varying economic developments (Kim, Matthes and Phan 2021). For instance, using country-specific macroeconomic data[4], Doyle and Noy (2013) examined the short-run impact of natural disasters (earthquakes) on New Zealand's consumer price index (CPI) – they found that inflation fell as natural disasters reduced aggregate

[2] Climate shocks refers to weather conditions, such as temperature and precipitation exceeding a specific average or extreme weather events such as storms, droughts and floods.

[3] The hurricane belt is an area in the Atlantic Ocean which is likely to get hurricanes during the Atlantic hurricane season.

[4] For example, real GDP growth, gross fixed capital formation, interest rate differentials, international trade, exchange rate, unemployment, public (private) sector consumption, total investment and net migration data.

demand. Using data on temperature, CPI, country-specific measures of sectoral activity and a Bayesian VAR (to allow for climate-inflation non-linearities) Ciccarelli, Kuik and Hernández (2023) found that, in the Euro Area, higher temperatures increased inflation in the summer – the converse holds for the other remaining seasons. Finally, Mukherjee and Ouatarra (2021) constructed a panel dataset (comprising of 107 countries and information on real GDP, consumer prices, money supply, government spending and temperature changes) and, through a panel VAR, found that climatic shocks generally accelerated inflationary pressures across the world. Heinen et al. (2018), investigate how extreme weather can drive short-term price increases in 15 Caribbean islands. Using a monthly data set of potential hurricane and flood destruction indices and linking these with consumer price data, the results show that the expected price increase is on average small every month. However, for floods the expected monthly impact is larger and occurs more often but for a hurricane the resulting rise is considerably larger. Across the sub-categories of goods, both hurricanes and floods have the largest impact on food prices, while hurricanes only affect the price of housing.

Local projections (LPs), another popular technique in the literature, compares two conditional means of a future outcome given today's available information, one of which is *subject to an intervention while the other is not* (Jordà 2023). Based on the method, forecasts are a product of a sequence of regressions at monthly (or quarterly) horizons (Lee, et al. 2022). For instance, in Cevik and Jalles (2023) the LP method was used to evaluate the impact of weather-related events on economic growth and the CPI in 173 countries – results showed that high temperatures reduced inflation while droughts and storms raised inflation. Kabundi, Mlachila and Yao (2022) found, via LP, that the impact of natural disasters and historical changes in temperature (and precipitation) on CPI depends on: (i) type and severity of the event; (ii) country income level (162 countries were investigated in the study); and (iii) monetary policy regime. Notably, droughts had a significant increasing effect on inflation, primarily food inflation, while floods had a decreasing effect on inflation. For the latter result, which seems counter-intuitive, the authors attribute the dominance of a negative demand shock, induced by the risk adverse behavior of agents from the flood to have dampening effects on inflation. Additionally, overtime flexible inflation targeting policy regimes were ineffective in the face of climatic shocks. Finally, Faccia et al. (2021) ran local panel projections, to predict the impact of extreme temperatures on consumer and producer prices in 48 countries. They found evidence that warmer weather reduced inflation in the medium to long-run.

Survey research, which involves the collection of information from a sample of individuals through their responses to questions (Check and Schutt 2017), allows for reliable collection of data on human behaviour. Several studies examining the climate-price relationship also utilised survey data to gain insights on the channels. For instance, Meinerding, Poinelli and Schüler (2022) used microdata from the 'Bundesbank Online Panel – Households' (a monthly survey of German households' expectations for inflation, house prices and interest rates) to evaluate how perceptions of climate change could influence inflation expectations. The study found a strong negative correlation between inflation expectations and climate – notably, a one-notch decrease in climate concern increased inflation expectations. In another piece of survey research, Abe and Moriguchi (2013) investigated trends in the: (i) shopping patterns of 12,000 households; and (ii) transactions of 2,600 retail stores after the Great East Japan Earthquake. They found that Japan experienced a minimal increase in inflation, after this event, as excess demand was resolved by 'rationing by queuing' and 'quantity restrictions'.

As the literature continues to develop, there is no general consensus on the best approach to model the relationship between inflation and climate change. For instance, the Financial Stability Board (2021) noted that 32.0 per cent of financial authorities (in surveyed jurisdictions) reported that they lack data on firms' and households' asset locations and mortgage collateral – the absence of which make it difficult to verify physical risks. Despite the popularity of the aforementioned approaches, each method possesses inherent limitations. A major shortcoming of VARs are that they require large amounts of information to produce reliable forecasts (Bhattacharyya, Srivastav and Vaidya 2023), therefore, the occurrence of data gaps present challenges. Meanwhile, LPs generate significant variance at intermediate and long horizons (Herbst and Johannsen 2020, Li, Plagborg-Møller and Wolf 2022). Finally, when it comes to survey research, robustness may be impaired by the level of economic/financial literacy on climate change.

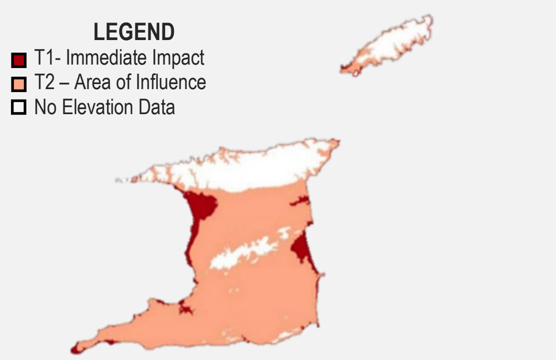
The lack of scholarly consensus in the inflation-climate arena which is important for prescribing strategic policy responses was reflected in the post-disaster monetary policy actions of the US Federal Reserve, the Bank of Japan and the Bank of Thailand. Batten, Sowerbutts and Tanaka (2020) noted that the US Federal Reserve increased interest rates after Hurricane Katrina (in 2005) while Bank of Japan and Bank of Thailand lowered their rates – following the Great East Japan Earthquake (in 2011) and Thailand Floods (in 2011). The discrepancy in actions may be due to economic fundamentals at the time of the natural disaster or a general lack of knowledge on how monetary policy should respond to climatic shocks.

In the literature, several authors also explored the possibility of a non-linear relationship between climate and the real economy (climate non-linearities). Sahuc et al. (2024) posit that climate change and climate change mitigation strategies have non-linear and long-lasting effects on both the supply and demand sides of the economy and the natural real interest rate (Sahuc, Smets and Vermandel 2024). To explore climate non-linearities, some researchers have used **DSGE techniques** to model risks from climate change. For instance, Batten and Millard (2024) designed a New Keynesian DSGE (NK-DSGE) to explore possible transition risks from efforts to reach net zero in the United Kingdom. They found that carbon taxes decreased economic agents' consumption of energy, while the effect of bans depended on the elasticity of substitution. Notwithstanding, net zero policies resulted in a temporary increase in inflation– raising the need to tighten monetary policy. Economides and Xepapadeas (2018) also used a NK-DSGE. This explored how climate change impacted the monetary policy of authorities that follow a Taylor rule. The model focused on the Euro Area and the results suggested that climate change increases the propagation of standard shocks. This lengthened the duration of the effects of disturbances–intensifying associated fluctuations in economic activity.

Stylised Facts

Trinidad and Tobago is an archipelagic state situated in the southern Caribbean. The total area of the country is approximately 5,131 km^2 – with Trinidad being the larger and more populous of the two. Further, roughly: (i) 44.0 per cent of Trinidad and Tobago is forested; (ii) 10.0 per cent is under agriculture; and (iii) 45.0 per cent is occupied by housing, commerce, industry and recreation (GORTT 2021). Both islands have some elevations. In Trinidad, they are found mainly along the northern shoreline, while Tobago's interior is covered by low mountains and a chain of hills. Notwithstanding, experts note that most of the country lies within the coastal zone **(Figure 1)**. Although this is not unusual for island nations, it indicates a high vulnerability to sea level rise and storm surges (GORTT 2019) – when it comes to natural disasters, hydrological events **(Figure 2)** had the highest frequency and cost.

Figure 1: Terrestrial Coastal Zones of Trinidad and Tobago, 2014

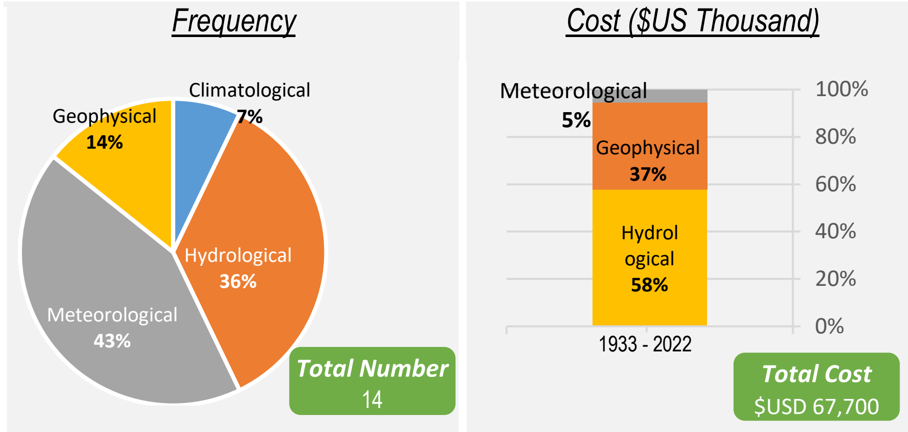


Source: Adapted from GORTT (2019)

Note: T1 (the 5meter contour)

T2 (the 5meter to 90 meter contour)

Figure 2: Natural Disasters, 1933 – 2022

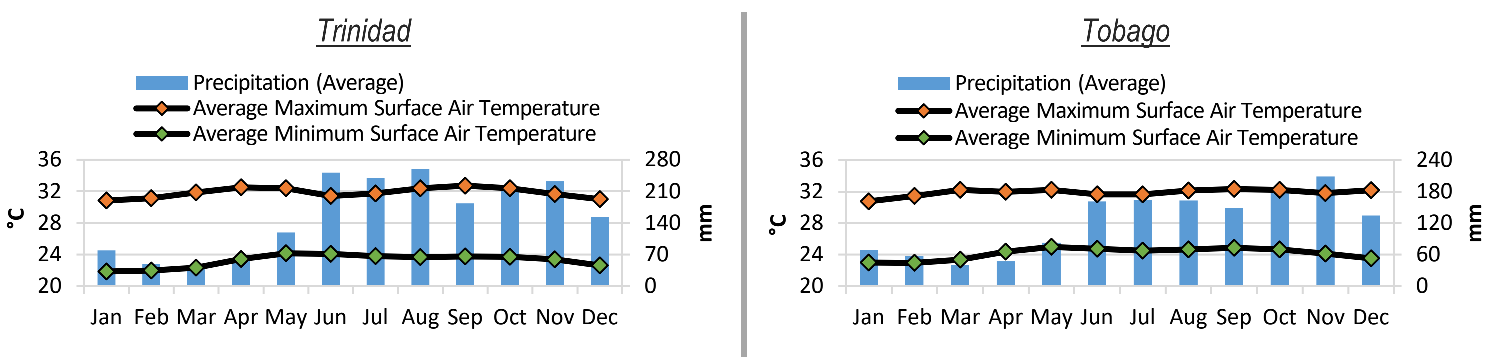


Source: Adapted from EM-DAT (an international disaster database)

Note: Meteorological (example storms); Hydrological (example floods); Climatological (example droughts); Geophysical (example earthquakes).

The World Bank Group (2019) noted that Trinidad and Tobago experiences two distinct climate types: (i) tropical maritime (characterised by warm days, cool nights and low rainfall); and (ii) modified moist equatorial (characterised by hot days/nights and high rainfall). Trinidad and Tobago's Meteorological Service (TTMS) reported that this causes the country to experience two opposing seasons—dry (January to May) and wet (June to December). During the dry season, in Trinidad, temperatures fluctuate (on average) between 23°C and 32°C, and total rainfall (**Figure 3**) for some months can be as little as 1,637 millimeters (mm). Meanwhile, in Tobago temperatures fluctuate (on average) between 24°C and 31°C, and total rainfall for some months can be as little as 1,712 mm. In the wet season, in Trinidad, temperatures (on average) fluctuate between 24°C and 32°C and total rainfall for some months can reach as high as 10,895 mm—in Tobago temperatures fluctuate (on average) between 24°C and 31°C and the total rainfall for some months can reach as high as 8,577 mm.

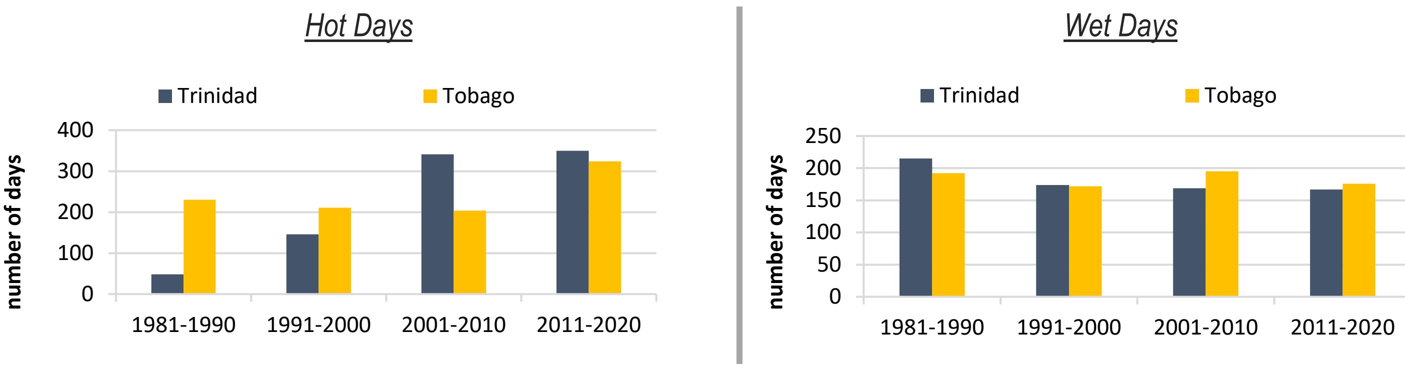
Figure 3: Average Monthly Max-Min Temperatures, 1981 – 2022



Source: TTMS

Note: Variations "*between the islands of Trinidad and Tobago are primarily as a result of difference in land size, orography, elevation, orientation in terms of the trade winds and geographical location*" (TTMS 2022).

Figure 4: Extreme Heat/Rain, 1981 – 2022



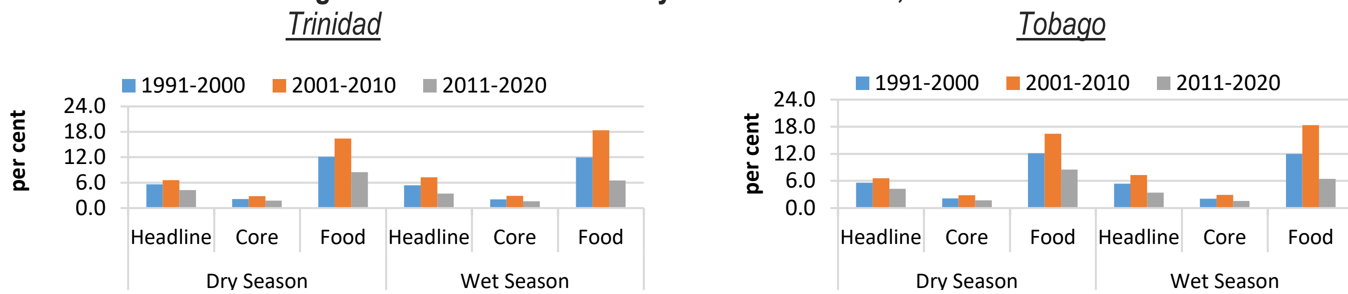
Source: TTMS
Note: Hot (wet) days occur when maximum temperature (total rainfall) reach or exceed the 95th percentile (Carvalho and Wanderley 2022, TTMS 2022).

"*Temperatures in Trinidad and Tobago have been found to have increased steadily from 1946 to 1995*" (TTMS 2016). The study further notes that over the last three decades, temperatures have displayed an upward trend. This was fuelled by a gradual increase in daily minimum temperatures—increases on average each year, between 1981 and 2022, by 0.01°C (in Trinidad) and 0.02°C (in Tobago). These increases in temperature have resulted in a steady increase in the number of hot days **(Figure 4)**.

"*Changes in rainfall differ across various parts of the country and over different time periods*" (TTMS 2016). TTMS (2016) found that annual rainfall totals in Trinidad and Tobago increased, between 1960 and 1980, but subsequently decreased in the 1990s. Further, consistent with the decline in the number of wet days overtime there has been fractional decreases in rainfall over the last 50 years **(Figure 4**).

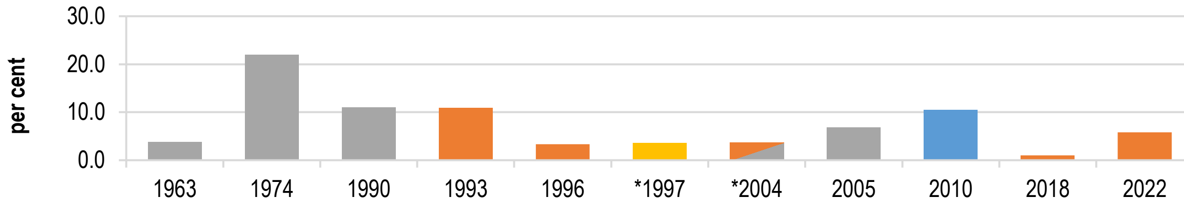
The impact of the change in Trinidad and Tobago's weather patterns on inflation is unclear (**Figure 5**). Across both islands, all categories of inflation increased over the decennial period 2001-2010, with inflation particularly higher for food during the wet season. However, during the decennial period 2011-2020 inflation rates fell but food inflation remained elevated and was higher in the dry season across both islands. Notwithstanding, it should be noted that Trinidad and Tobago experienced some of its highest inflation rates during climate-related stress events (**Figure 6**). **Figure 6** shows that while Trinidad and Tobago has experienced a mix of climate-related stress events, as of late (within the last century) the country has experienced more climatological and hydrological events.

Figure 5: Inflation over the Dry and Wet Seasons, 10-Year Intervals



Source: Central Statistical Office

Figure 6: Inflation during Periods Marked by Climatic-Related Stress Events



Source: Central Statistical Office and EM-DAT

Note: The colours of the columns represent if the event was **Meteorological**, **Hydrological**, **Geophysical**, or **Climatological** in nature. *Experienced two climatic-related stress events.

Methodology and Data

To evaluate the impact of climate change on inflation the paper uses VECM modelling. Similar to Mukharjee and Quatarra (2021), a VAR model is adopted in the first instance using data from first quarter 1991 to fourth quarter 2022. Given the possibility of long-term climate impacts, cointegration is examined using the Johansen cointegration test, and then VECM is employed. The VAR model is specified as follows:

$$Zy_t = W + \Gamma(L)y_{t-1} + \varepsilon_t \qquad \text{Equation 1}$$

Where y_t is the vector of n endogenous macroeconomic and climate change variables. Specifically: international food prices (FAO); Output (Y) - computed as year-on-year changes in the Quarterly Index of Real Economic Activity (QIEA); government revenue (GR)[5]; headline inflation (INF) – measured as changes in the consumer price index (CPI); food inflation (FI); core inflation (CI)[6]; money supply (M2); temperature (TEMP); precipitation (RNF); wet days (WD); hot days (HD); and a dummy variable (D3), which takes the value of 1 for the occurrence of a natural disaster (storms, droughts and floods) according to the Emergency Events Database (EM-DAT) and 0 otherwise[7] (**Appendix 1)**.

The matrix Z is an $n \times n$ matrix of contemporaneous coefficients of y_t; W denotes the $n \times 1$ vector of constant; $\Gamma(L)$ is the $n \times n$ matrix of lag operator polynomials which captures the lags of the endogenous variables; and ε_t is the $n \times 1$ vector of white noise processes that is normally distributed with a mean 0 and variance of 1 (that is, $\varepsilon_t \backsim N(0,1)$). To maintain the stability of the model and minimise the 'noise', each inflation variable (headline, food and core) was included in an individual VAR along with the other macroeconomic variables[8]. The model specification is guided by the theories of cost-push inflation, demand-pull inflation and the Structuralist model of imported inflation (Greenidge and DaCosta 2009). The FAO variable reflects world food prices and its inclusion in the model captures the transmission of international food prices to domestic food prices, particularly given our high dependency on

[5] Broader fiscal variables such as the overall fiscal balance (OFB), structural fiscal balance (SFB) and the cyclically adjusted fiscal balance (CAB) were considered. However, due to challenges with utilising the OFB as well as lack of data on one-off revenue and expenditure items to compute the SFB and CAB, these measures were not considered in the model.

[6] Changes in the CPI provides a measure of headline inflation, which comprises both food and core inflation. Core inflation is a measure of underlying inflation and omits all food components.

[7] EM-DAT is a joint initiative between the Centre for Research on the Epidemiology of Disasters (CRED) and the World Health Organization (WHO). D3 is a binary variable which takes the value of 1 for the occurrence of a natural disaster such as storms, droughts and floods and 0 otherwise.

[8] Three models were estimated in the paper. Each model included a different measure of inflation. Model 1 includes headline inflation (HI), model 2 – Food inflation (FI), and model 3 –core inflation (CI).

imports. This price relationship has been verified by several authors in the literature, including Nelson and Cox (2024). Output, among other variables, are repeatedly seen as important to the inflation process from the literature. As such, output is deemed to capture demand pressures in the economy, since increasing output indicates that demand pressures are present and inflation is increasing. The GR[9] and the M2 are also incorporated in the model to reflect fiscal and monetary policy and to examine the interplay between these key policy variables and inflation. Meanwhile, the inclusion of TEMP, follows from the Structuralist school of thought where inflation may be a consequence of weather conditions and trading or protection policies (Greenidge and DaCosta 2009). This is supported by the growing body of research which finds that climate has added to the inflation momentum in recent years (Heinen, Khadan and Strobl 2018).

Results and Analysis

Correlation Analysis[10]

The cross-correlation of the variables specified in the model was evaluated using Pearson Correlation to assess their association with inflation. Correlation values between the inflation variables and climate variables are very weak. In spite of the very weak association, across the three measures of inflation, headline inflation holds the strongest association with the climate variables in the model, excluding WD and RNF **(Table 1)**. Between food and core inflation, food inflation is more correlated with TEMP, WD and D3 while core inflation is more correlated with HD. All climate variables have a positive association with headline, food and core inflation[11]. This positive association implies that shocks related to climate events could increase inflation. Meanwhile, the correlation values between the macroeconomic variables and components of inflation span from moderate to strong in intensity.

Table 1
Correlation Matrix

	INF	FI	CI	FAO	GR	M2	Y	TEMP	RNF	HD	WD	D3
INF	1.00	1.00	0.98	0.77	0.82	0.98	-0.52	0.11	0.04	0.19	0.09	0.04
FI	1.00	1.00	0.98	0.75	0.77	0.95	-0.55	0.06	0.04	0.15	0.10	0.03
CI	0.98	0.98	1.00	0.76	0.81	0.98	-0.52	0.04	0.04	0.18	0.09	0.02
FAO	0.77	0.75	0.76	1.00	0.24	0.28	0.42	-0.41	0.21	0.21	0.00	0.11
GR	0.82	0.77	0.81	0.24	1.00	0.87	-0.28	0.27	0.11	0.31	0.11	0.00
M2	0.98	0.95	0.98	0.28	0.87	1.00	-0.48	0.17	0.03	0.24	0.07	0.00
Y	-0.52	-0.55	-0.52	0.42	-0.28	-0.48	1.00	-0.04	0.01	-0.13	-0.04	0.01
TEMP	0.11	0.06	0.04	-0.41	0.27	0.17	-0.04	1.00	0.23	0.77	0.23	-0.07
RNF	0.04	0.04	0.04	0.21	0.11	0.03	0.01	0.23	1.00	0.22	0.91	0.04
HD	0.19	0.15	0.18	0.14	0.31	0.24	-0.13	0.77	0.22	1.00	0.20	0.03
WD	0.09	0.10	0.09	0.00	0.11	0.07	-0.04	0.23	0.91	0.20	1.00	0.03
D3	0.04	0.03	0.02	0.11	0.00	0.00	0.01	-0.07	0.04	0.03	0.03	1.00

[9] In Trinidad and Tobago, Government revenue is found to be highly correlated with net domestic fiscal injection (NDFI), a major driver of liquidity compared to Government expenditure. NDFI was omitted from the model due to unavailability of data prior to 2000.
[10] Notably, intensity and direction can change depending on the treatment of variables as well as the period of analysis.
[11] Correlation coefficients between: (i) 0 and 0.2 are regarded as **very weak**; (ii) 0.2 and 0.4 are regarded as **weak**; (iii) 0.4 and 0.6 are regarded as **moderate**; (iv) 0.6 and 0.8 are regarded as **strong**; and (v) 0.8 and 1 are regarded as **very strong**. +/- indicates the direction (same/opposite) of the correlation.

Stationarity Analysis

The variables were evaluated for stationarity using the Augmented Dickey-Fuller (ADF) Test and the Phillips Perron (PP) Test. The results of the unit root tests are presented in **Appendix 2**. With the exception of Y and D3, which were stationary at level, all other variables were found to be integrated of order one (I (1)). Provided that VAR models require stationary variables, all I(1) variables were differenced (times one) to be made stationary **(Appendix 3)**. Following the estimation of the VAR, several model authenticity checks were undertaken to ensure reliability. The estimated models were normally distributed, and the residuals are free from serial correlation and heteroscedasticity. The results of the lag order selection criteria also suggest 5 lags were sufficient to remove autocorrelation and heteroscedasticity from the model. The VAR model was also evaluated for cointegrating relationships using the Johansen Cointegration test. The results of the same suggest at most four cointegrating equations among the variables **(Appendix 3)**. As such, VECM modelling was employed, subject to the same robustness checks[12].

Model Results

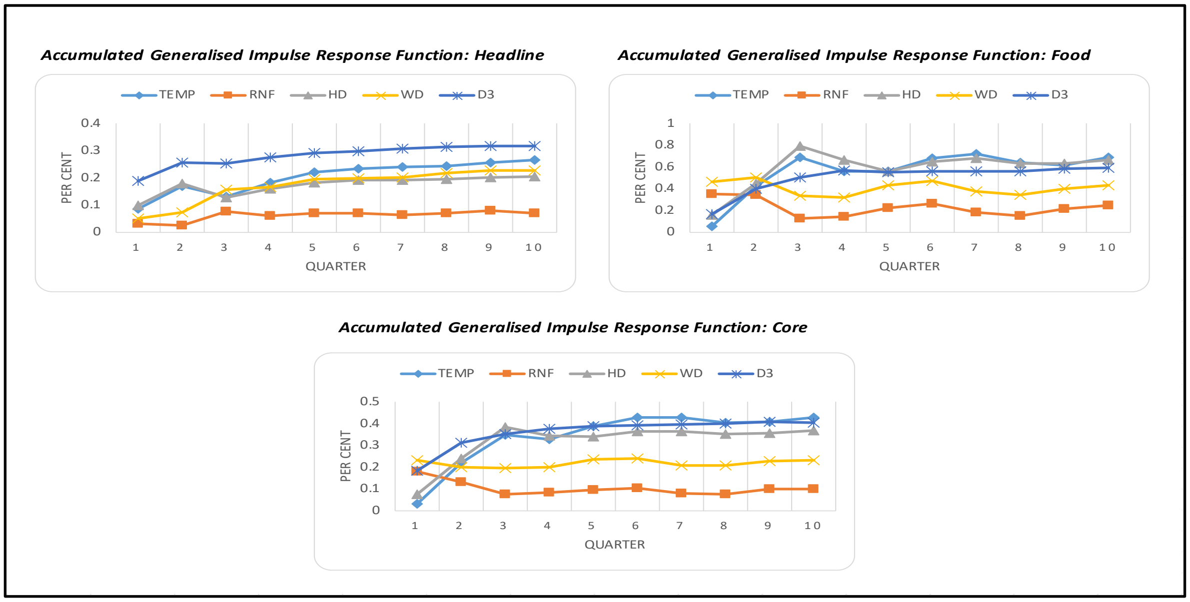
To trace the effects of climate shocks on inflation, the VECM framework is evaluated using Impulse Response Functions (IRFs) with a generalised ordering[13] **(Figures 7 and 8)**. From the IRF we find that food, core and headline inflation respond positively to climatic shocks in the short and long-run. More specifically, higher TEMP, RNF, WD, HD and D3 increases food, core and headline inflation in the short-run. The findings are consistent with the literature, including Mukherjee and Quatarra (2021) and Heinen et al. (2018). In the long-run, headline, food and core inflation respond positively to climatic shocks – TEMP, RNF, HD and WD.

Analysing the impact of climate-related shocks on food and core inflation is important from a policy perspective. The increasing effect of TEMP, RNF, HD and WD on food inflation, in both the short-run and long-run carries implications for the agriculture sector where output is highly sensitive to climate. Specifically, temperature and precipitation can determine crop yields and thereby influence prices. The Food and Agriculture Organisation identifies direct, indirect, and socio-economic effects of climate change which increase with increasing climate events **(Appendix 5)**. This effect was evident in the 2024 dry season when farmers complained of intense heat waves affecting crop yields and alluded to higher prices. In April and May 2024, vegetable prices surged, occasioning an overall increase in food and headline inflation. Additionally, in October and November 2022, increased precipitation, which led to bouts of flooding across the country, also resulted in a rise in vegetable prices which underpinned an increase in food inflation and overall headline inflation.

[12] VECM requires variables to be integrated of the same order. Provided that Y and D3 are I(0), they were omitted from the estimation. ARDL allows for the use of I(0) and I(1) variables, however, because a VAR forecasting framework is adopted in house, consideration was given to VECM in the first instance. It should be noted that model authenticity checks on VECM model 2 revealed Heteroskedasticity at the 1.0 and 5.0 per cent level of significance, possibly relating to climatic non-linearities in the data.

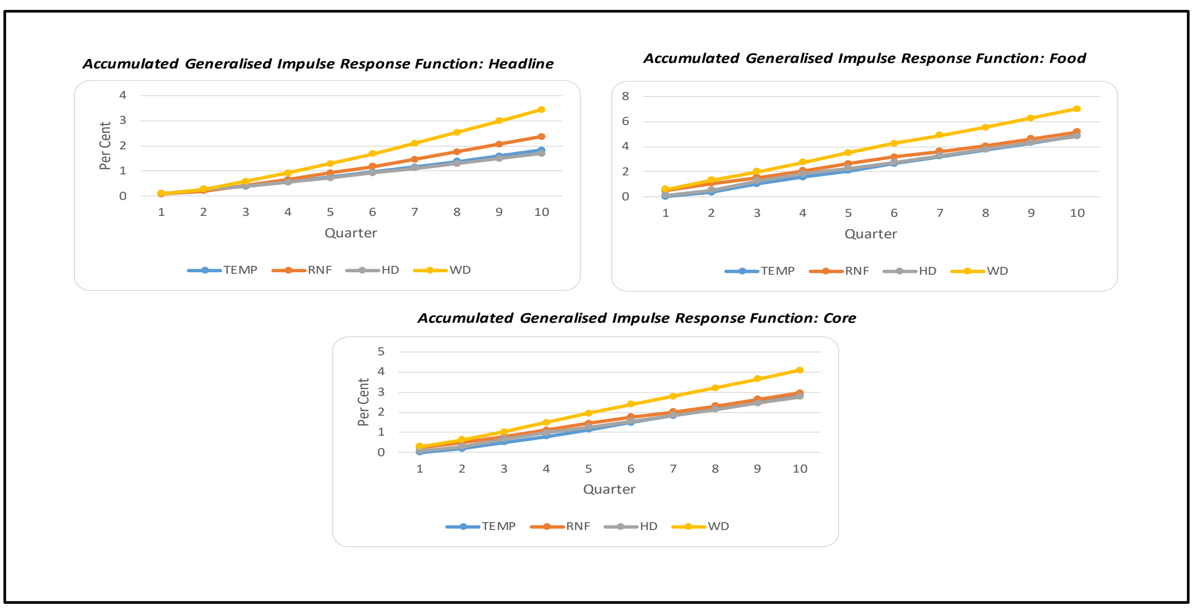
[13] VECM is a restricted VAR designed for use with nonstationary series that are known to be cointegrated. Given the sparse literature on studies that have employed the VAR and VECM methodologies to explore the response of inflation to shocks, particularly for small open developing economies (see for example, Christiano et al. 2005), the generalised impulse response ordering was adopted.

Figure 7
Accumulated Generalized Impulse Response Functions of Inflation from a Shock to Climate Variables (Short-run)



The figure show IRFs using the VAR method. x-axis in quarters; t=0 is the year preceding the climate shock; t=1 is the first year of impact.

Figure 8
Accumulated Generalized Impulse Response Functions of Inflation from a Shock to Climate Variables (Long-run)



The figure show IRFs using the VECM method. x-axis in quarters; t=0 is the year preceding the climate shock; t=1 is the first year of impact.

The link between climate shocks and core inflation is less clear when compared to food inflation. Climate-related events can impact core inflation directly or indirectly[14] or can be of a long-term nature. Climate related events can impact sub-indices within core inflation such as Recreation and Culture, Transport, Health, and Housing, Water, Electricity and Gas **(Appendix 6)**. Climate change in Trinidad and Tobago, specifically hotter days can lead to higher demand for electricity which can indirectly increase firms' operating expenses across different sectors which can be reflected in different sub-indices within core inflation. Nonetheless, fuel and electricity prices are administered by the state and do not adjust automatically, thus core inflation is only directly impacted when deliberate adjustments are made to retail prices. For instance, in 2023, the Trinidad and Tobago Weather Centre reported that Trinidad and Tobago recorded extremely hot temperatures and was under a prolonged heat wave. During the period, Trinidad and Tobago broke its eight-year electricity consumption record twice, as residential customers increased their use of air conditioning units to manage the temperature rise[15]. Despite the increase in electricity usage, there was no increase in retail prices and by extension core inflation. Meanwhile, in April and October 2022 when the price of fuels at the pump increased to reduce expenditure on the fuel subsidy, there was an uptick in prices in the Transport sub-index and in core inflation. This led to second round effects namely increases in taxi and maxi taxi fares.

Analysing the impact of D3, on headline, food, and core inflation in the short-run is pivotal, provided that natural disasters including, storms, floods and droughts can significantly affect consumer prices across sectors, and can pull prices and output in opposite directions. From the perspective of the central bank, this would mean any attempt to lower inflation could further reduce output because of the existing trade-off between price and output stability. Additionally, consideration must be given to the possible price slowdown that can arise through the demand channel (lower aggregate demand) from policy shifts that may result due to the occurrence of a natural disaster. This was evident in Doyle and Noy (2013). Therefore, calibrating monetary policy and the banks' reaction function to this shock will have to carefully consider these trade-offs.

The response of Y to TEMP was also analysed in the model **(Appendix 7 and 8)**. According to the results of the IRFs, temperature shocks were found to affect output negatively, in the short-run. A long-run response was not calibrated as Y is a stationary in its level form[16]. The finding is consistent with several studies such as Rosenzweig and Parry (1994) and Barrios et al. (2008) which provide quantitative evidence of the damaging effect of climate change on output, and its increasing effects on prices[17]. The aforementioned studies carry implications for the long-term productive capacity of the economy. Higher temperatures and increasing adverse weather events can dampen economic activity and reduce labour productivity. Singh et al. (2023) noted that climate change can also increase the incidence of diseases, and can increase mortality rates which have implications for long-term human productivity[18].

The response of inflation to other macroeconomic variables such as the FAO and Y were also considered. In the case of the FAO, a shock to FAO has an instantaneous positive impact on headline inflation in the short-run and long-run,

[14] Direct impact influences the consumer price index (CPI) and its sub-indices while indirect impact arises from pass through effects to some good or service captured in the CPI. Long-term impact refers to those pass-through effects that impact inflation through changes in aggregate demand or supply conditions.

[15] See Newspaper Article for additional details: https://www.cnc3.co.tt/electricity-usage-record-broken-twice-as-people-beat-the-heat/

[16] VECM requires that all variables be integrated of the same order (integrated of order one I (1)). With the use of an Autoregressive Distributed Lag (ARDL) model, variables that are I (0) and I (1) can be modelled together. However, because the inflation forecasting framework in-house is based on the VAR Methodology, ARDL was not considered.

[17] While several studies in the literature have identified a decreasing effect between temperature and output, it is important to note that the converse is not true as lower temperature does not imply higher output. In fact, over the years, output has increased with temperature increasing. As such, in examining a temperature and output relationship, it would be important to include the channels through which this relationship operate for example examining temperature and agriculture output as oppose to temperature and aggregate output.

[18] Climate change further increases outbreak risks by altering pathogen evolution and host–pathogen interactions, facilitating the emergence of new diseases.

consistent with the literature, including Mahabir and Jagessar (2011) and Nelson and Cox (2024). The response of headline inflation to output was found to be deflationary in the short-run. The decreasing effect, could imply that the expansion in output could be supply driven resulting in an overall deflationary effect on headline inflation. The response of inflation to fiscal and monetary policy (GR and M2) were also analysed in the model. In the case of GR, a one standard deviation shock, is found to increase inflation in the short and long-run. Given the procyclical nature of fiscal policy in Trinidad and Tobago this result was anticipated (Cotton, Finch and Sookraj 2013). Higher revenue leads to increased fiscal injection from higher expenditure, increasing aggregate demand and inflation. In the case of M2, expansionary monetary policy increases headline inflation in both the short-run and long-run **(Appendix 7 and 8)**, verifying the use of monetary policy tools in managing inflation.

VAR Framework – Inflation Forecasting

The second objective of the paper is to determine whether there is increased predictive gain from the inclusion of climate variables in the inflation process. The development and use of economic models to forecast inflation in-house dates back to the 1980s with the commencement of the Trends, Analysis and Projections (TAP) exercise. TAP, which was eventually replaced with the International Monetary Fund's Financial Programming and Policies (FPP) Framework in 2010, was subsequently modified in 2017 to produce quarterly forecasts. Forecasts are estimated over a three-year horizon and forecast evaluations are undertaken annually. Over the years several measures utilising statistical and econometric techniques were developed to forecast inflation. These indicators included, an inflation diffusion index (IDI), a composite leading indicator (CLI) of inflation and a Consumer Confidence Index (CCI). The aforementioned measures gave an indication on the direction of future inflation but did not provide information on the size of the change. Additionally, several econometric approaches such as VARs and VECMs were utilised as satellite models to forecast inflation.

In 2023, the inflation forecasting methodology, which was predominantly judgment-based was revised as part of the 2023 FPP forecasting exercise. The new approach adopted a combination of econometric modelling and statistical techniques to derive quarterly inflation forecasts. In the case of the econometric modelling, VAR is employed to make out-of-sample forecasts of both core and food inflation. Using the estimates of core and food inflation, a weighted summation is used to derive headline inflation. **Table 2** below provides a snapshot of the forecast performance of inflation for 2023 utilising the current methodology and an overview of the forecast performance (2020-2022) based on the previous methodology which was largely expert judgment. The endogenous and exogenous variables included in the model for forecasting core and food inflation include; the output gap[19] (YGAP), exports and imports reflected by the current account balance (CAB), private sector credit (PSC), government revenue (GR)[20], West Texas Intermediate (WTI) prices, the unemployment rate (UR), United States (US) real GDP, and international food prices (FAO). The variables included in the model help account for inflation volatility and heterogeneity that can come from different determinants. Based on the forecast errors, it is evident that the size of the errors increased during periods of exogenous shocks, shocks for which the model was not accounting for, including, the COVID-19 pandemic, Russia's invasion of Ukraine and climatic events such as flooding which occurred in the fourth quarter of 2022. As

[19] The output gap is estimated by subtracting potential output from actual output and is expressed as a percentage of potential output. A negative output gap implies actual GDP is less than potential GDP while a positive output gap implies actual GDP is greater than potential GDP.

[20] Government revenue is selected to reflect the fiscal variable given that revenue and expenditure generally follow a procyclical path, therefore, higher revenues lead to higher government spending which affects liquidity conditions and employment and growth outcomes.

such, it had become clear that much of the volatility in inflation is still not being accounted for, therefore it has become pivotal to account for climatic shocks in inflation modelling.

Table 2
Inflation Forecast Performance (Per Cent)

	Quarterly Forecasts																Annual Forecast			
	2020	2020	2020	2020	2021	2021	2021	2021	2022	2022	2022	2022	2023	2023	2023	2023	2020	2021	2022	2023
	Q1	Q2	Q3	Q4	Q1	Q2	Q3	Q4	Q1	Q2	Q3	Q4	Q1	Q2	Q3	Q4				
Forecast	0.5	0.5	0.5	0.6	0.9	1.1	1.3	1.7	4.0	5.0	5.1	5.4	7.1	6.5	6.1	5.9	0.6	1.3	5.0	**6.4**
Actual	0.4	0.6	0.5	0.8	0.8	1.4	2.3	3.7	4.0	4.9	6.1	8.0	7.8	5.8	4.2	1.1	0.6	2.0	5.8	**4.6**
Forecast Error	0.1	-0.1	0.0	-0.2	0.1	-0.3	-1.0	-2.0	0.0	0.1	-1.0	-2.6	0.7	-0.7	-1.9	-4.8	0.0	-0.7	-0.8	**-1.8**

Source: Central Statistical Office and Central Bank of Trinidad and Tobago
Note: Actual data sourced from Central Statistical Office. Forecasts are sourced from Central Bank of Trinidad and Tobago's Financial Programming and Policies (FPP) forecasting exercise.

Many models of inflation build on the Phillips curve relationship between inflation and economic activity. Inflation fluctuations reflect aggregate demand pressures on productive capacity, temporary supply shocks and changes in inflation expectations. Since climate-related variables were found to have positive effects on inflation, these variables were incorporated into the inflation forecasting equation to determine whether they enhance model prediction. The Root Mean Squared Error (RMSE)[21], Mean Absolute Error (MAE)[22], and Theil Inequality Coefficient are used to evaluate forecast accuracy. These measures were computed for each of the three models (headline, food and core inflation). The models with climate variables are referred to as VAR_C, while the models without climate variable are referred to as VAR. The models' summary forecast performance measures based on in-sample forecasts computed over the period 2020Q1 to 2022Q4 are presented in **Table 3**. Evaluation of the RMSE, MAE and Theil coefficient suggest enhanced predictability when climate variables are incorporated in the inflation modelling equation[23]. The summary measures associated with the forecasts of food, core and headline inflation in the model that include climate variables were lower when compared to the models without climate variables. **Appendix 9** provides a plot of actual and forecast of core inflation for VAR and VAR_C[24]. From the plots it can be seen that VAR_C predicts core inflation with greater forecast accuracy. The ability to forecast other macroeconomic/climate variables accurately was also assessed. From the analysis, it is also clear that incorporating climate change also improves the model's ability to forecast other macroeconomic variables such as GR and M2. Since VAR_C improves the forecast accuracy for models predicting headline, food and core inflation, the study confirms that accounting for climate can improve the Bank's forecast of inflation and support monetary policy analysis. As such, climate variables can be included in the

21 The root mean squared error (RMSE), which takes the square root of the average of the sum of the squared forecast errors was utilised.
22 The Mean Absolute Error (MAE) measures the average difference between the model's predicted values and the actual values.
23 A lower RMSE, MAE, MAPE, and Theil coefficient imply greater forecast accuracy.
24 Model 3 which includes forecast of core inflation was selected based on the model's forecast performance across all three measures and variables.

Bank's forecasting exercise to provide out-sample forecast of inflation over a three-year forecast horizon. This will be beneficial as it would account for any increased volatility stemming from climate change.

Table 3
Model Forecast Performance Summary Measures

	VAR			VAR_C		
Variable	**RMSE**	**MAE**	**Theil**	**RMSE**	**MAE**	**Theil**
Model 1						
INF	1.044	0.64	0.59	1.04	0.64	0.59
FAO	5.35	4.34	0.81	5.38	4.33	0.82
GR	1878.63	1557.30	0.73	1741.63	1494.74	0.70
M2	0.01	0.01	0.53	0.01	0.01	0.46
Y	8.30	6.92	0.89	8.40	7.03	0.89
Model 2						
FI	3.00	1.91	0.62	2.92	1.88	0.60
FAO	4.99	3.84	0.71	5.40	4.28	0.84
GR	1815.40	1512.12	0.76	1733.16	1475.31	0.71
M2	0.01	0.01	0.52	0.01	0.01	0.46
Y	8.05	6.68	0.89	8.21	6.86	0.89
Model 3						
CI	1.043	0.64	0.59	1.04	0.64	0.59
FAO	5.35	4.34	0.81	5.38	4.33	0.82
GR	1878.63	1557.30	0.73	1741.63	1494.74	0.70
M2	0.01	0.01	0.53	0.01	0.01	0.46
Y	8.30	6.92	0.89	7.46	5.81	0.81

RMSE: Root Mean Square Error
MAE: Mean Absolute Error
Theil: Theil inequality coefficient
Cells shaded blue reflects lower errors when compared to the VAR model without climate variables. Cell not shaded are greater than or equal to VAR model without climate variables.

Climate Scenario

Provided that there is a need to understand how climate change is likely to alter inflation volatility as there is already noticeable increases in the number of hot days and a decrease in the number of wet days, a scenario of increased warming (a mean temperature of *1.5°C*) is calibrated to show how climate-related disasters frequency, flooding, dryness and economic activity in climate-sensitive sectors such as agriculture, construction and transport can be impacted. For this exercise, Autoregressive Integrated Moving Average with eXogenous inputs (ARIMAX) are utilised **(Appendix 10)**. With a mean temperature change for the next three years (2023 to 2025) of 1.5°C, a total of 370 climate-related disasters per year is projected **(Figure 10)**. On average international meat and cereal prices could increase by 2.5 per cent and 9.0 per cent, respectively yearly. For Trinidad and Tobago, the warmer global temperature could cause the country to experience on average 222 incidences of dryness (a total of 188 in 2022) and 15 occurrences of flooding each year.

Annual CO_2 emissions fell by 1.1 per cent each year possibly relating to the size of the increase in global temperature and the conscious effort to restrain temperatures to below 1.5°C. Meanwhile, agriculture activity fell by 2.2 per cent each year possibly due to increased dryness and flooding. Construction and Transport activity on the other hand grew on average by 5.5 per cent and 4.9 per cent respectively each year. The increase in construction and transport activities may be on account of the dry weather conditions, usually considered to be favourable. Additionally, with the fall in annual CO_2 emissions, and higher activity in the transport sector, a sector considered to be a major generator of CO_2 emissions, it shows that carbon reduction strategies does not impede growth[25]. The results suggest that agriculture activity will be the most impacted and could result in food inflation reaching as high as 14.7 per cent possibly on account of flooding. Core inflation on the other hand, is projected to reach around 3.2 per cent. Collectively, these developments resulted in an average headline inflation rate of 6.0 per cent over the forecast horizon.

The efficacy of the scenario was evaluated based on how well it predicted pre- and post-pandemic inflation (**Appendix 11).** For ease of interpretation emphasis is placed on the Mean Absolute Percentage Errors (MAPEs)[26]. Although there were some exceptions (for example, the pre-pandemic core inflation MAPE was quite large), in most cases the ARIMAX produced forecasts with MAPEs in accordance with Chen, Bloomfield and Fu (2003)—particularly for 2023. The results suggest that climate variability does shape the inflation outturn. Therefore, warming can influence the rate at which prices are rising and impact climate-sensitive sectors.

[25] Based on a study which identified the industry, transport and power generation sectors as major producers of CO_2 emissions. CRS _Strategy_Final.pdf (planning.gov.tt)

[26] To judge the accuracy of the forecast—less than 10 per cent is a highly accurate forecast, 11 to 20 per cent is a good forecast, 21 to 50 percent is a reasonable forecast, and 51 per cent or more is an inaccurate forecast (Chen, Bloomfield and Fu 2003).

Figure 10: ARIMAX Scenario

SPECIFICATIONS

GLOBAL ENVIRONMENT CONSIDERATIONS: Mean Temperature Change of Meteorological Year, ***1.5°C***

Climate-related Disasters Frequency, ***370***

LOCAL ENVIRONMENT CONSIDERATIONS: Dryness Indicator, ***222 occurrences***

Flooding Indicator, ***15* occurrences**

Annual CO2 emissions, ***33.3 million tonnes***

ECONOMIC ACTIVITY INDICATORS: QIEA Index: Agriculture, yoy growth, ***-2.2 per cent***

QIEA Index: Construction, yoy growth, ***5.5 per cent***

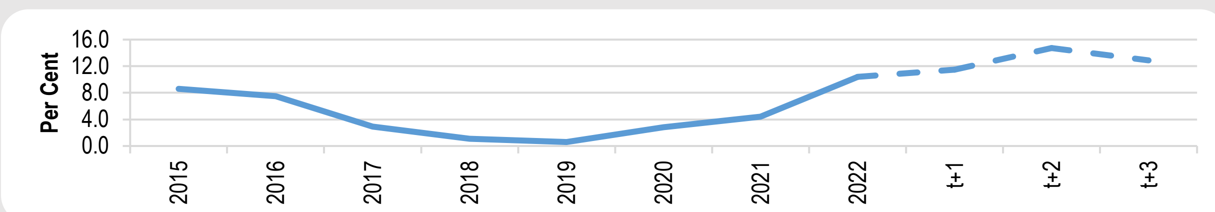
QIEA Index: Transport, yoy growth, ***4.9 per cent***

FAO Meat Price Index, ***2.5 per cent***

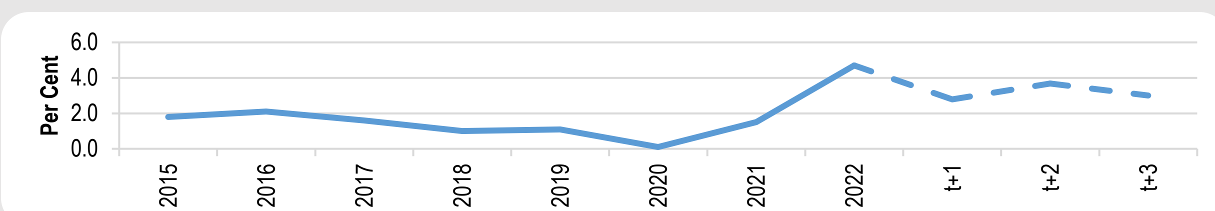
FAO Cereals Price Index, ***9.0 per cent***

RESULTS

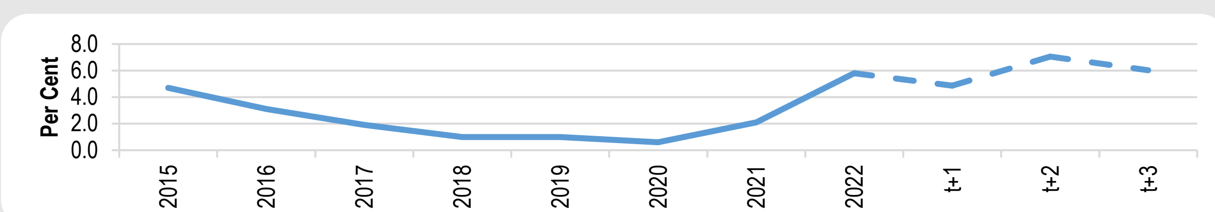
Food Inflation



Core Inflation



Headline Inflation



Note: Numbers presented in **bold** and *italics* are the three year averages.

Conclusion and Recommendation

Climate change has led to increased scientific research on the impact of this phenomenon on prices. This paper investigates the impact of climate change on inflation and evaluate whether there is predictive gain from its inclusion in inflation forecasting. The study confirms climate change has added to the price momentum over the years. Food inflation, core inflation and headline inflation increase in response to climatic shocks in the short-run and long-run. More specifically, higher TEMP, RNF, WD, HD and D3 increase food, core and headline inflation in the short-run. Meanwhile, all variables with the exception of D3 increase food inflation, core inflation and headline inflation in the long-run. Considering the impact of TEMP on output, higher temperature reduces output in the short-run. In the case of other macroeconomic variables, higher international food prices and expansionary fiscal and monetary policy, all lead to higher prices in the short-run and long-run. The paper also confirms that incorporating climate change in the inflation forecasting methodology can improve the Bank's inflation forecast. Additionally, scenario analysis based on assumptions of increased warming suggests that climate variability can influence the rate at which prices are rising and impact climate-sensitive sectors.

The study contributes to the literature on 'climateflation' - the inflationary impacts of a warming planet. The results of the paper carry useful implications for central banks and macroeconomic modelling in general. The upward pressures on inflation from weather-related shocks, especially if occurring under increased frequency due to climate change can increase inflation volatility. This in turn may pose challenges to inflation forecasting and monetary policy, likely increasing the difficulty of identifying temporary supply shocks and disentangling them from other drivers that may be more persistent.

The presence of increased predictive gain from including climate variables in inflation forecasting strongly highlights the importance for central banks to consider climate change in their macroeconomic assessment and forecasting tools. More persistent upward inflationary pressures due to climate change could render the identification of drivers of inflation more difficult when relying on traditional models. As a result, central banks may need to consider weather and climate shocks in inflation forecasting. Weather and climate shocks could therefore be considered a permanent feature of the inflation dynamics and not transitory. Additionally, increasing upward inflation pressure could have adverse effects on purchasing power, and disproportionately push vulnerable groups into poverty. Weather and climate shocks can intensify the trade-off between price stability and growth objectives and would require an understanding of the mechanics of the climatic shock (size of the shock, time it takes for the effects to decay) at play to achieve optimal monetary policy. Therefore, coordinated monetary, fiscal and supply-side policies will be required to maintain price stability.

While this study identified several weather-related variables with significant impacts on inflation and its various components, there were some limitations to providing a comprehensive relationship between weather conditions and inflation. In the study domestic prices reflect imported and local production, therefore assessments of spill-overs via international food prices provide interesting insights. However, having more granular data such as local prices reflecting domestic production could provide some insights on imported inflation. Additionally, other measures of prices such as producer prices are significantly outdated as the measure has a base year of 1978, undermining its utility as an indicative measure of wholesale prices. In light of the following, there is the need for development of prices data that reflects local production as well as up-to-date producer price indices to comprehensively account for domestic wholesale prices.

There is also the need to explore climatic non-linearities in the dataset. The VAR model approach adopted assumes constant variance and makes certain Gaussian assumptions of the coefficients and model parameters. However, the impact of climate change could be non-linear as weather conditions change suddenly. Input and output do not respond proportionately and there may be multiple equilibria. As such, techniques that consider these characteristics and utilise non-Gaussian assumptions such as a threshold VAR, regime-switching VAR or non-parametric techniques to explore climate non-linearities should be considered[27]. However, having explored additional approaches (such as Bayesian VAR and Autoregressive Distributed Lag (ARDL)) to treat with the characteristics of the dataset, the models returned similar results. The results of the model estimation seem sensitive to the period of analysis, the size of the dataset, the methodology adopted and the variables utilised.

The research provides a foundation for future research on climate and inflation, particularly as we adopt strategies for a green future. Possible research areas such as 'greenflation', which refers to inflationary pressures stemming from the implementation of climate mitigation policies to reach a low-carbon economy can be explored.

[27] The Bayesian non-parametric VAR is a flexible model that is able to account for nonlinear relationships as well as heteroscedasticity in the data.

References

Abe, Naohito, and Chiaki Moriguchi. 2013. "The Effects of Natural Disasters on Prices and Purchasing Behaviors: The Case of Great East Japan Earthquake." *Asia-Pacific Economic Association.*

Barrios, Salvador , Bazoumana Ouattara , and Eric Strouble. 2008. "The impact of climatic change on agricultural production: Is it different for Africa?" *ELsivier* 287-298.

Batten, Sandra, Rhiannon Sowerbutts, and Misa Tanaka. 2020. "Climate Change: Macroeconomic Impact and Implications for Monetary Policy." *Bank of England.*

Bhattacharyya, Rutan, Ashish Kumar Srivastav, and Dheeraj Vaidya. 2023. "Vector Autoregression." *WallStreetMojo, Statistics Guides.*

BoE. 2024. "Energy and Climate Policy in a DSGE Model of the United Kingdom." *Bank of England, Staff Working Paper No. 1,064.*

Carvalho, Leticia Vicente, and Henderson Silva Wanderley. 2022. "Risk Identification of Precipitation Extremes due to Climate Change in the Southern Region of the State of Rio de Janeiro." *Revista Brasileira de Geografia Física.*

CBTT. 2022. "Financial Stability Report, 2021." *Central Bank of Trinidad and Tobago.*

Cevik, Serhan, and João Tovar Jalles. 2023. "Eye of the Storm: The Impact of Climate Shocks on Inflation and Growth." *International Monetary Fund, IMF Working Paper.*

Check, Joseph, and Russel K Schutt. 2017. "Research Methods in Education." *Sage Research Methods.*

Christiano, Lawrence J, and Martin Eichenbaum. 2005. *Nominal Rigidities and the Dynamic Effects of a Shock to Monetary Policy.* Accessed 2024.

Ciccarelli, Matteo, Friderike Kuik, and Catalina Martínez Hernández. 2023. "The Asymmetric Effects of Weather Shocks on Euro Area Inflation." *European Central Bank, Working Paper Series, No 2798.*

—. 2023. "The Outlook is Mixed: The Asymmetric Effects of Weather Shocks on Inflation." *European Central Bank, Research Bulletin No.111.*

CIMH. 2018. "Country Profile: Trinidad and Tobago." *Caribbean Institute for Meteorology and Hydrology, World Meteorological Organization, Environment and Climate Change Canada.*

Cotton, Jason, Kevin Finch, and Rekha Sookraj. 2013. "Measuring the Cyclically Adjusted and Structural Balances in Trinidad and Tobago." *Central Bank of Trinidad and Tobago.*

Deryugina , Tatyana, and Solomon Hsiang. 2014. "Temperature and Income in the United States." Accessed 2024.

Doyle, Lisa, and Ilan Noy. 2013. "The Short-run Nationwide Macroeconomic Effects of the Canterbury Earthquakes." *Victoria Business School, Victoria University of Wellington.*

Drudi, Francesco , Emanuel Moench, Cornelia Holthausen, Pierre-François Weber, Gianluigi Ferrucci, Ralph Setzer, Virginia Di Nino, et al. 2021. "European Central Bank." *Climate Change and Monetary Policy in the Euro Area, ECB Occasional Paper No. 2021/271.* Accessed 2014.

Economides, George, and Anastasios Xepapadeas. 2018. “Monetary Policy under Climate Change.” *Munich Society for the Promotion of Economic Research, CESifo Working Papers.*

Eric. 2021. “Introduction to the Fundamentals of Vector Autoregressive Models.” *Data Analytics Blog.*

Faccia, Donata, Miles Parker, and Livio Stracca. 2021. “Feeling the Heat: Extreme Temperatures and Price Stability.” *European Central Bank, Working Paper Series, No. 2626.* Accessed March 2024.

Felbermayr , Gabriel , and Jasmin Groschl . 2013. “Natural disasters and the effect of trade on income: A new panel IV approach.” *European Economic Review* 18-30.

Felmine, Kevon. 2023. *Electricity usage record broken twice as people beat the heat.* Accessed 2024.

FSB. 2021. “The Availability of Data with Which to Monitor and Assess Climate-Related Risks to Financial Stability.” *Financial Stability Board.*

GCF. 2015. “The Earth Statement.” *Global Challenges Foundation.*

GEC. 2018. “Central Banks Should Lead by Example on Transparency and Climate Change.” *Green Economy Coalition, Reforming Financial Systems.*

GORTT. 2021. “First Biennial Update Report.” *Government of the Republic of Trinidad and Tobago, To The United Nations Framework Convention on Climate Change.*

—. 2019. “Vulnerability and Capacity Assessment (VCA) Report, Trinidad and Tobago.” *Government of the Republic of Trinidad and Tobago, EUROPEAID/136530/DH/SER/TT.*

Greenidge, Kevin , and Dianna DaCosta. 2009. “Determinants of Inflation in Selected Caribbean Countries.” *Business Finance and Economics in Emerging Economies.* Accessed 2024.

Heinen, Andreas, Jeetendra Khadan, and Eric Strobl. 2018. “The Economic Journal.” *The Price Impact of Extreme Weather in Developing Countries.* Accessed 2024.

Herbst, Edward P, and Benjamin K Johannsen. 2020. “Bias in Local Projections.” *Federal Reserve Board, Finance and Economics Discussion Series.*

Jagessar, V, and R Mahabir. 2011. “Central Bank Working Paper 02/2011.” *An Examination of the Import Price Transmission Mechanism in Trinidad and Tobago.*

Jones, Benjamin F, and Benjamin A Olken. 2010. “Climate Shocks and Exports.” *National Bureau of Economic Research.* Accessed 2024.

Jordà, Òscar. 2023. “Local Projections for Applied Economics.” *Federal Reserve Bank of San Francisco, Working Paper Series 2023-16.*

Kabundi, Alain, Montfort Mlachila, and Jiaxiong Yao. 2022. “How Persistent are Climate-related Price Shocks?” *International Monetary Fund, WP/22/207.*

Kim, Hee Soo, Christian Matthes, and Toan Phan. 2021. “Extreme Weather and the Macroeconomy.” *Social Science Research Network.*

Kotz, Maximilian , Friderike Kuik , Eliza Lis , and Christiane Nickel. 2024. “Global warming and heat extremes to enhance inflationary pressures.” March. Accessed 2024.

Kotz, Maximilian, Friderike Kuik, Eliza Lis, and Christiane Nickel. 2023. "The Impact of Global Warming on Inflation: Averages, Seasonality and Extremes." *European Central Bank, Working Paper Series, No. 2821.*

Kotzé, Kevin. 2019. "Vector Autoregression Models." *Github.*

Lagarde, Christine . 2021. *Climate change and central banking.* Accessed 2024.

Lee, Sinyoung O, Nelson C Mark, Jonas Nauerz, Jonathan Rawls, and Zhiyi Wei. 2022. "Global Temperature Shocks and Real Exchange Rates." *University of Notre Dame.*

Li, Dake, Mikkel Plagborg-Møller, and Christian K Wolf. 2022. "Local Projections vs. VARs: Lessons from Thousands of DGPs." *MIT Economics.*

Lindsey, Rebecca, and Luann Dahlman. 2022. "Climate Change: Global Temperature." *National Oceanic and Atmospheric Administration, Climate.gov, Understanding Climate.*

Mann, Catherine L. 2023. "Climate Policy and Monetary Policy: Interactions and Implications." *Bank of England.*

Meinerding, Christoph, Andrea Poinelli, and Yves Schüler. 2022. "Inflation Expectations and Climate Concern." *Deutsche Bundesbank, Discussion Paper, No 12/2022.*

Mukherjee, K, and B Ouattara. 2021. "Climate and Monetary Policy: Do Temperature Shocks Lead to Inflationary Pressures?" *Springer Link, Climatic Change.*

Munich Re. 2022. "Hurricanes, Cold Waves, Tornadoes: Weather Disasters in USA Dominate Natural Disaster Losses in 2021." *Munich Re Group .*

Nelson, Andell, and Delvin Cox. 2024. *Measuring Price Spillovers: An Investigation of Relative Prices.* Accessed 20245.

Network for Greening the Financial System. 2020. *Annual report.* Accessed March 2024.

Noel, Dorian. 2023. "Dealing with Inflation Dynamics in Trinidad and Tobago." *Central Bank of Trinidad and Tobago.* Accessed February 2023.

Quade, Gratianne. 2023. "Global Sea Surface Temperatures Reach Record High." *Mercator Ocean International.*

Rahaman, Akeem, and Reshma Mahabir. 2016. "Alternative Monetary Policy Rules in Trinidad and Tobago:An Analysis using a GMM approach." Accessed April 2024.

Raza, Ali, Ali Razzaq, Sundas Saher Mehmood, Xiling Zou, Xuekun Zhang, Yam Lv, and Jinsong Xu. 2019. "Impact of Climate Change on Crops Adaptation and Strategies to Tackle Its Outcome: A Review." Accessed 2024.

Rosenzweig, C, and M Parry. 1994. "Potential impact of climate change on world food supply." *Nature 367, 133–138* 133-138.

Sahuc, Jean-Guillaume, Frank Smets, and Gauthier Vermandel. 2024. "The New Keynesian Climate Model." *European Central Bank.*

SEC. 2022. "SEC Proposes Rules to Enhance and Standardize Climate-Related Disclosures for Investors." *U.S Securities and Exchange Commission, Press Release.*

Singh, Brajesh K, Manuel Delgado-Baquerizo, Eleonora Egidi, Emilio Guirado, Jan E Leach, Hongwei Liu, and Pankaj Trivedi . 2023. *Climate change impacts on plant pathogens, food security and paths forward.* May. Accessed 2024.

Trinidad and Tobago Express Newspaper. 2024. *Farmers brace for harsh dry season.* Accessed March 2024.

Trinidad and Tobago Weather Center. 2023. *T&T Records Hottest Day For 2023 To Date.* Accessed 2024.

TTMS. 2022. "Climate." *Trinidad and Tobago Meteorological Service.*

UNCC. 2020. "What is the Paris Agreement." *United Nations Climate Change, UNFCCC Process, The Paris Agreement.*

UNEP. 2021. "UNEP FI's Comprehensive Good Practice Guide to Climate Stress Testing." *United Nations Environment Programme.*

WBG. 2019. "Trinidad and Tobago - Climatology." *World Bank Group, Climate Change Knowledge Portal.*

Weder, di Mauro B. 2021. *Combatting Climate Change: A CEPR Collection, CEPR Press.* Accessed 2024.

WMO. 2022. "2021 One of the Seven Warmest Years on Record, WMO Consolidated Data Shows." *World Meteorological Organization, Press Releases.*

Appendices

Appendix 1
Data Description

Variable	Acronym	Data Source	Measurement
Headline Inflation	INF	Central Statistical Office	CPI Quarterly Index Value
Food and Agricultural Organisation Food Price Index	FAO	Food and Agricultural Organisation	FAO Quarterly Index Values
Government Revenue	GR	Ministry of Finance	Millions Trinidad and Tobago Dollars
Output	Y	Central Bank of Trinidad and Tobago	Year-on-Year Per Cent Change
Money Supply	M2	Central Bank of Trinidad and Tobago	Millions Trinidad and Tobago Dollars
Temperature	TEMP	Trinidad and Tobago Meteorological Society	Degrees Celsius
Precipitation	RNF	Trinidad and Tobago Meteorological Society	Millimetres
Dummy 3	D3	Caribbean Research Centre on Epidemiology and Diseases	Binary variable reflection 1 for a natural hazard, 0 otherwise
Hot Days	HD	Trinidad and Tobago Meteorological Society	No. of Days maximum temperature exceed 95th percentile (34.0 Degrees Celsius)
Wet Days	WD	Trinidad and Tobago Meteorological Society	No. of days precipitation exceed 95th percentile (>1mm)
Core Inflation	CI	Central Statistical Office	Core Quarterly Index Values
Food Inflation	FI	Central Statistical Office	Food Quarterly Index Values

Appendix 2

Results of the Unit Root Test

Variable	Acronym		First Difference
Headline Inflation Rate	INF		√
Food and Agriculture Organisation Real Food Price Index	FAO		√
Government Revenue	GR		√
Output	Y	√	
Money Supply	M2		√
Temperature (Degrees Celsius)	TEMP		√
Precipitation (Millimetres)	RNF		√
Dummy	D3	√	√
Hot Days	HD		√
Wet Days	WD		√
Core Inflation	CI		√
Food Inflation	FI		√

Appendix 3
Model Authenticity Checks

Models	VAR Stability	No. of Lags	No Serial Correlation	No Heteroskedasticity	Johansen Cointegration	VEC Error Correction Term	VECM Stability	VECM No Serial Correlation	VECM No Heteroskedascity
VAR									
Model 1 comprise the variables: INF; FAO; GR; M2; Y; TEMP; RNF; HD; WD; D3	√	5	No Serial Correlation	No Heteroskedascity					
Model 2 comprise the variables: FI; FAO; GR; M2; Y, TEMP, RNF, HD, WD; D3	√	5	No Serial Correlation	Yes Heteroskedascity					
Model 3 comprise the variables: CI; FAO; GR; M2; Y, TEMP, RNF, HD, WD, D3	√	5	No Serial Correlation	No Heteroskedascity					
VECM									
Model 1 comprise the variables: INF; FAO; GR; M2; TEMP, RNF, HD, WD					At most 4*	At least 1 significant ECT	√	No Serial Correlation	No Heteroskedascity
Model 2 comprise the variables: FI; FAO; GR; M2; TEMP, RNF, HD, WD					At most 4*	At least 1 significant ECT	√	No Serial Correlation	Yes Heteroskedascity
Model 3 comprise the variables: CI; FAO; GR; M2; TEMP, RNF, HD, WD					At most 4*	At least 1 significant ECT	√	No Serial Correlation	No Heteroskedascity

Source: Authors' Construction

ECT- Error Correction Term

* 1% level of significance

**5% level of Significance

***10 % level of significance

Appendix 4
VECM Methodology

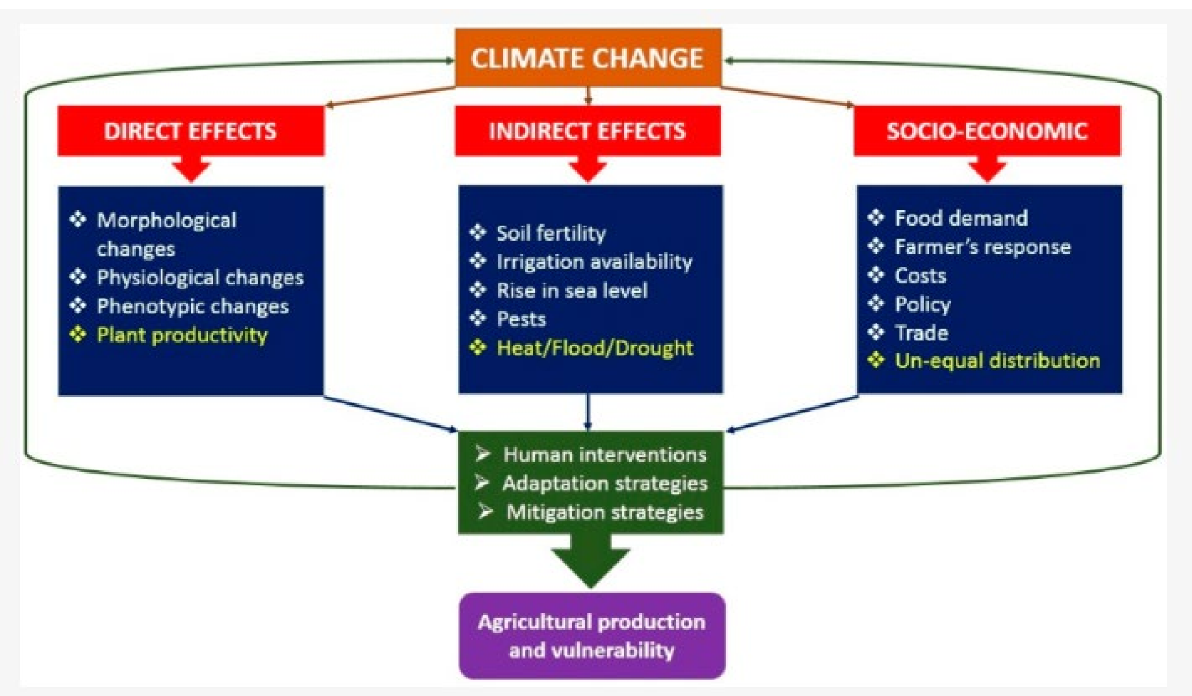
Given the results of the Johansen Cointegration, which suggest at most four cointegrating relationship, Vector Error Correction Modelling (VECM) was employed. VECM is a restricted VAR designed for use with nonstationary series that are known to be cointegrated. Hamilton (1994) describes an (nx1) vector time series yt as being cointegrated if each of the series are I(1), that is nonstationary with an order of integration of one, while some linear combination of the series a'yt is stationary or I(0) for some nonzero (nx1) vector a. The VECM has cointegration relations built into the specification so that it restricts the long-run behaviour of the endogenous variables to converge to their cointegrating relationships while allowing for short-run adjustment dynamics. The cointegration term is known as the error correction term since the deviation from long-run equilibrium is corrected gradually through a series of partial short-run adjustments. The VECM model specified is of the form:

$$\Delta y_t = \sum_{t=1}^{k-1} \Gamma_i \Delta y_{t-i} + \Pi y_{t-k} + \varepsilon_t \qquad \text{(Equation 1)}$$

Where y_t is an nx1 vector of endogenous variables, which includes the macroeconomic variables specified in the VAR[28]. ε_t is an nx1 vector of stochastic disturbances and Π a matrix whose rank r gives the statistical properties of the Vector Autoregression (VAR) Π=αβ^t where α is an nx1 matrix of speed of adjustment parameters and β is an nxr matrix of parameters which determines the cointegrating relationship.

Appendix 5

Direct, Indirect and Socio-Economic Effects of Climate Change on Agricultural Production



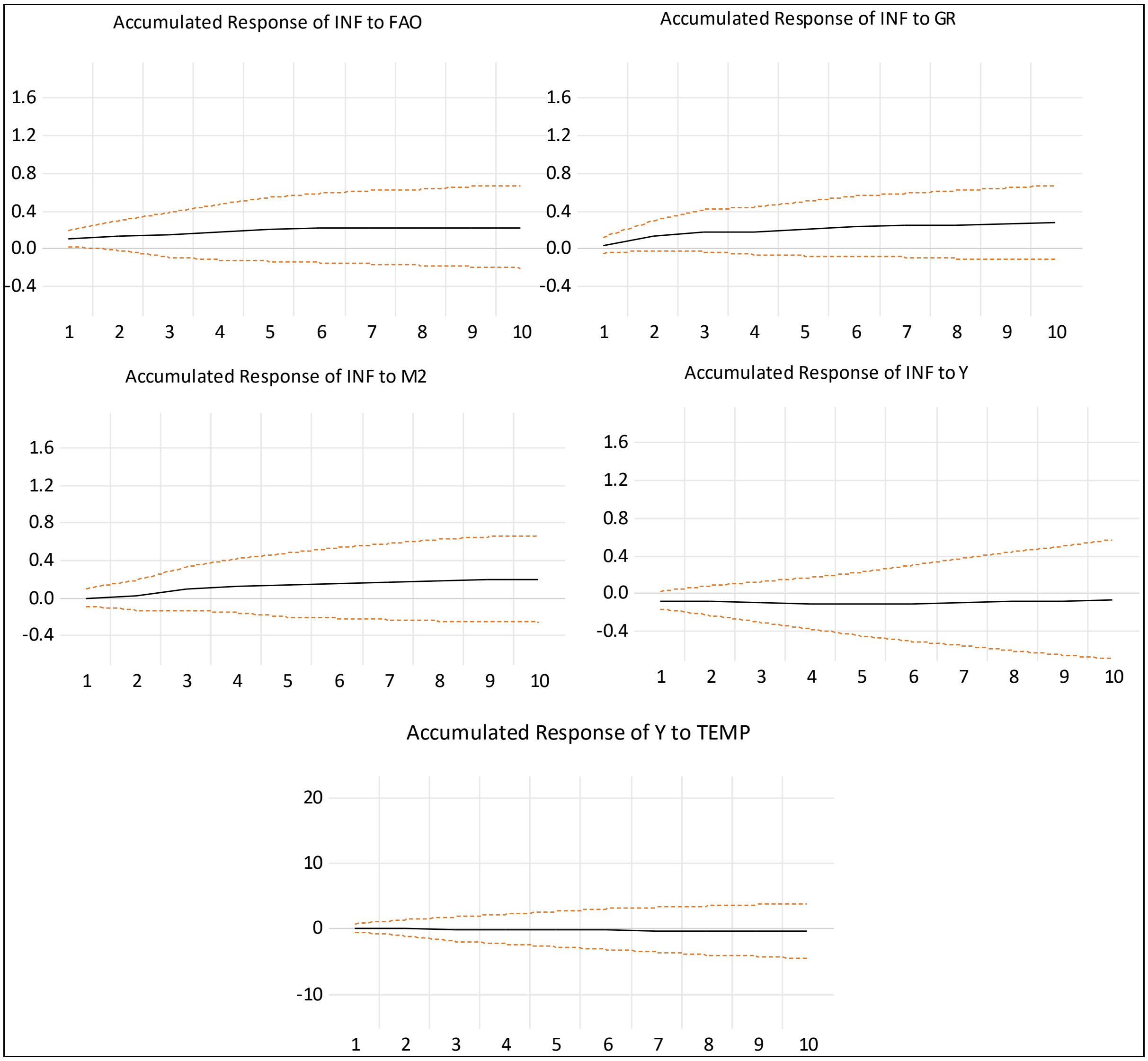
Source: Food and Agriculture Organisation

[28] Three models were calibrated using the standard macroeconomic variables and a different measure of inflation. Model 1 which is the main model includes INF, model 2 – FI and model 3 –CI.

Appendix 6
Core Inflation Sub-Indices likely to be Impacted from Climate Shocks

Housing, Water, Electricity, Gas and Other Fuel	• Painting • General Masonry • Water Rates • Electricity Rates
Furnishing, Household Equipment and Routine Maintenance	• Household Appliances • Small electrical Appliances • Cleaning Products
Health	• Prescription Medication • Over the Counter Pharmaceutical Products • Other Medical Products
Recreation	• Garden, Plants and Flowers • Animal Husbandry • Veterinary Expenses
Transport	• Fuels and other lubricants • Transport by sea • Transport by air
Miscellaneous	• Articles and products for personal care

Appendix 7
Accumulated Generalised Impulse Response Function of Selected Macroeconomic Variables (Headline) (Short-run)



Source: Eviews Output

The exhibit shows IRFs using the VAR method for Model 1. x-axis in quarters; t=0 is the year preceding the shock; t=1 is the first year of impact. The solid black line denotes the response, the red dotted line denotes the confidence bands.

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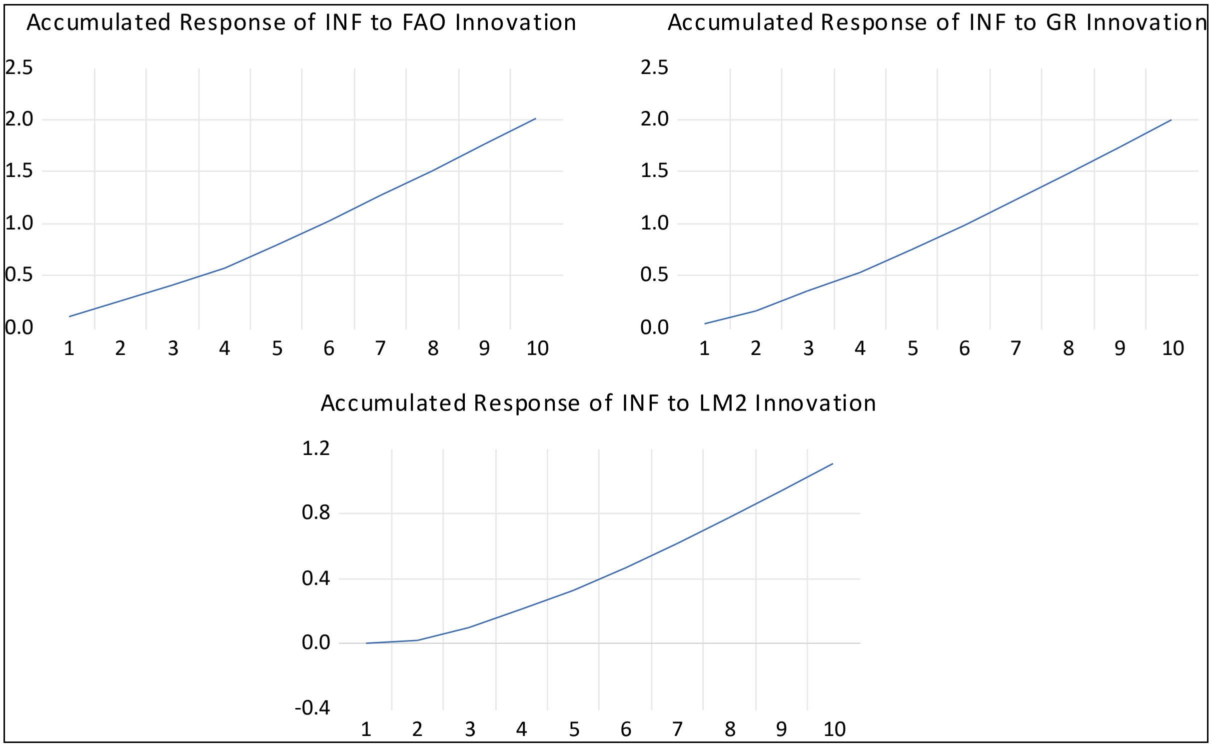
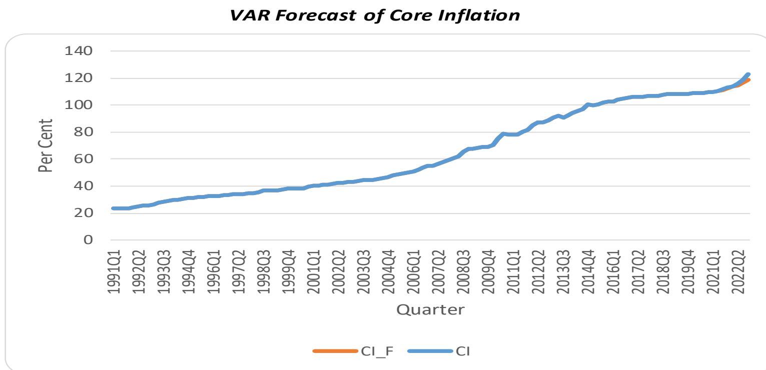
Appendix 8
Accumulated Generalised Impulse Response Function of Selected Macroeconomic Variables (Model 1) (Long-run)

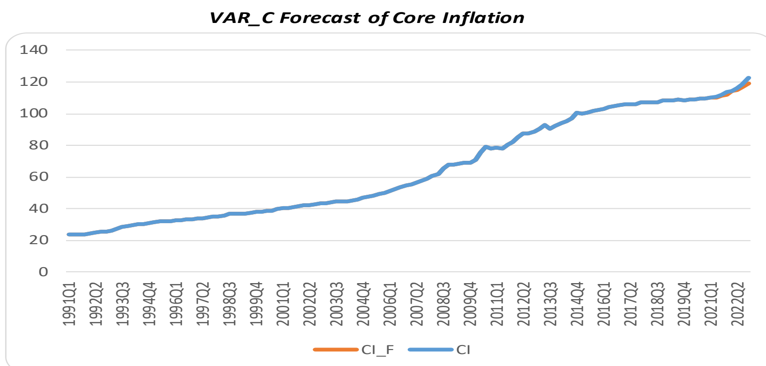


Source: Eviews Output

The exhibit shows IRFs using the VECM method for Model 1. x-axis in quarters; t=0 is the year preceding the shock; t=1 is the first year of impact. The solid blue line denotes the response.

Appendix 9
Model Forecast Performance (Core Inflation Index Value)





Source: Authors' Construction

Appendix 10
Technical Annex ARIMAX

The ARIMAX model allows for projecting the future values of a series based on its own inertia and some group of theoretically consistent exogenous variables. The general ARIMAX model is represented as follows:

$$Z_t = \varphi_0 + \sum_{i=1}^{p} \varphi_i Z_{t-i} + \sum_{i=1}^{d} \gamma_i X_{t-i} + \sum_{i=1}^{q} \beta_i \varepsilon_{t-i}\, \varepsilon_t \qquad \textbf{Equation 2}$$

Where:

- Z_t is the variable of interest;
- X_t is a vector of exogenous variables;
- p denotes the order of autoregression;
- q denotes the order of moving average; and
- d denotes the order of integration

The model specification and variable selection process was an iterative process guided by the Akaike Information Criterion. Further refinements were made based on forecast accuracy. Specifically, ex-ante prediction test statistics were constructed to estimate how well the ARIMAX models predicted inflation (and its various categories) over the pre-pandemic, pandemic, and post-pandemic periods. This is used to evaluate how well the ARIMAX deals with unanticipated exogenous shocks. The period of analysis is 1991 to 2022. The annual frequency allowed us to incorporate climate variables that were previously omitted in the VAR and VECM models in section 4. For example, in this exercise, annual carbon dioxide emissions (CO2) were incorporated. This allows for the inclusion of a source variable in our assumption that global warming is behind the intensification of environmental conditions. Other indicators utilised in the model includes: mean temperature, a climate-related disaster frequency indicator, a dryness indicator, a flooding indicator, real GDP growth for agriculture, transport and construction, the FAO Meat Price Index, the FAO Cereal Price Index, headline inflation, food inflation and core inflation **(Table 1)**.

From the suite of indicators, physical risks from flooding and dryness could impair activity in agriculture, construction and transport. Additionally, international meat and cereal prices along with economic activity in the agriculture sector are expected to impact food inflation, particularly given the significant weight of bread and cereals and meats in the food component of the CPI. Meanwhile, given Trinidad and Tobago's commitments to its Nationally Determined Contributions (NDCs), decarbonisation is likely to continue—impacting the activities of sectors that produce CO2 emissions. Core inflation alike would also be impacted given impaired activity on sectors such as construction and Transport, impacting core components of the CPI such as Transport, Furnishing, Household Equipment and Routine Maintenance and Recreation and Culture. Headline inflation is expected to be impacted by changes in both food and core inflation

Table 1
ARIMAX, Exogenous Variables

Variable	Description	Reason for Inclusion	Source	Adjustments
World: Mean Temperature Change of Meteorological Year	*Annual estimates of mean surface temperature change.*	"*Global warming causes climate change*" (National Geographic 2022).	International Monetary Fund	-
World: Climate-related Disasters Frequency	The number of climate-related disasters over time.	"*Since droughts and severe storms erode production potential and disrupt economic activity across wider areas, their economic bearings are likely to be pronounced*" (Fuje, et al. 2023).	International Monetary Fund, EM-DAT	-
Trinidad and Tobago: Annual CO2 emissions	Annual total emissions of carbon dioxide.	"*Through ratification of the Paris Agreement, Trinidad and Tobago will have to reduce cumulative greenhouse gas emissions by 15.0 per cent*" (UN 2018).	Our World in Data	-
Dryness Indicator	"*According to WMO a dry spell is a period of at least 15 consecutive days none of which received 1 mm or more*" TTMS (2016).	"*A report from CRED & UNDRR (2021) comparing the number of disasters in 2020 with the average data from 2000 to 2019 shows an increase in natural disasters worldwide…. the most significant changes are observed in the amount of precipitation and the duration of droughts*" (Furtak and Wolińska 2023).	Trinidad and Tobago Meteorological Service	An annual dummy variable may not perform well in a forecasting model. As such the 'Dryness Indicator' captures the number of days with less than 1mm of rain. The 'Flooding Indicator' captures the number of days with more than 25 mm of rain.
Flooding Indicator	"*Putting rainfall forecasts into context, rainfall rates in excess of 50 millimeters per hour or areas that receive in excess of 25 millimeters within an hour tend to trigger street flooding across the country or flash flooding in*			

	northern Trinidad" (TTWG 2019).			
QIEA Index: Agriculture, yoy growth **FAO: Meat Price Index** **FAO: Cereals Price Index**	'Vegetables' and 'fruit' make up approximately 17.2 per cent of the total weight of the 'food and non-alcoholic beverages' sub-index (food inflation index). Meanwhile, 'Bread, cereal and cereal preparation' and 'meat' account for approximately 36.9 per cent of the 'food and non-alcoholic beverages' sub-index.	Global warming will intensify harsh environmental conditions. This will impact agricultural output/yield—influencing food inflation. Given our large share of import content in the food component of the CPI, meat and cereal price conditions were proxied using FAO data. Several publications note a large food import bill (Silva 2020, CSO 2023, Gittens 2023).	Food and Agriculture Organization	-
QIEA Index: Construction, yoy growth	'Housing electricity gas and other fuels' and 'transport' sub-indices account for approximately 51.1 per cent of the weight of the core inflation index.	Global warming will intensify harsh environmental conditions. This will hamper productivity. Further, "*Trinidad and Tobago is also committed to conditionally reduce its cumulative carbon emissions by 15 per cent in the power generation, transport and industrialised sectors by 2030*" (GORTT 2018).	Central Bank of Trinidad and Tobago	-

Appendix 11
Forecast Accuracy Tests, Scenario Assumptions

Statistic	Description	2023 Period			2019 to 2022 Period			2017 to 2019 Period		
		Core Inflation	Food Inflation	Headline Inflation	Core Inflation	Food Inflation	Headline Inflation	Core Inflation	Food Inflation	Headline Inflation
Root Mean Square Error (RMSE)	The sample standard deviation between the predicted observations and the real historical observations. Lower values of the RMSE indicate better forecast accuracy.	1.11	3.78	0.27	1.59	2.02	1.53	0.49	4.57	1.4
Mean Absolute Error (MAE)	The average of the absolute difference between the predicted observations and the real historical observations. Lower values of the MAE indicate better forecast accuracy.	1.11	3.78	0.27	1.35	1.22	1.35	0.4	3.38	1.01
Mean Absolute Percentage Error (MAPE)	Measures the size of the difference between the predicted observations and the real historical observations in percentage terms.	28.6	49.12	5.79	465.6	12.9	102.94	21.6	98.3	48.12