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Short-Run Dynamics of Energy Consumption and Socioeconomic Drivers in Trinidad and Tobago: A Novel Approach using VAR Analysis

Sharona Mohammed*, Dillon Ramsook, Donnie Boodlal, Rean Maharaj

Department of Process Engineering, University of Trinidad and Tobago, Point Lisas, Couva, Trinidad and Tobago.
*Email: sharona.mohammed@utt.edu.tt

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ABSTRACT

Trinidad and Tobago (T&T), while a minor contributor to global greenhouse gas (GHG) emissions, ranks among the highest per capita emissions due to its fossil-fuel dependent economy and energy-intensive sectors. To support effective climate action under its Nationally Determined Contributions (NDCs), it is critical to understand how socioeconomic factors drive energy consumption and emissions. This study examined the dynamic relationship between key socioeconomic drivers (GDP and population) and energy consumption (electricity, LPG, diesel and gasoline) in T&T's residential and road transportation sectors using annual data from 2000 to 2023. Correlation analysis (Pearson and Spearman) assessed the strength and direction of the relationships, followed by time series techniques including unit root and Johansen cointegration tests, Granger causality and impulse response functions. Results showed strong correlations between electricity consumption for GDP and population, while diesel and gasoline were more closely linked to GDP. LPG showed weak, positive correlations with both drivers. The absence of long-run cointegration justified the use of a Vector Autoregression (VAR). Granger causality tests indicated weak causal relationships, except for electricity and population, where population shocks had a sustained impact on demand. This study presents a novel approach to GHG forecasting and supports the development of data-driven, sector-specific NDCs.

Keywords: Energy Demand Forecasting, VAR Modelling, Correlation Analysis; Socioeconomic Drivers, NDCs, SIDS
JEL Classifications: C32, C54, Q41

1. INTRODUCTION

The analysis of greenhouse gas (GHG) mitigation measures has grown increasingly significant as the global intensifies efforts to address the critical issue of climate change, with data showing global GHG emissions hitting a new high of 57.1 $GtCO_2e$ in 2023, up 1.3% (0.7 $GtCO_2e$) over the previous year (Crippa et al., 2024). The role of developing countries in global GHG reduction efforts has become significant due to their increasing GHG contributions, with the Sustainable Development Goals Report (2020) quoting an increase of 43.2% during the 2000 to 2013 period. This rise in GHG emissions was largely driven by industrialization, economic growth and urbanization, with fossil CO_2 emissions from energy and industrial processes accounting for about 68% of total emissions (UNEP, 2024).

As the impact of developing countries on global emissions increases, population size and growth rates will play a significant role in magnifying the effects of global warming. There is a mutual relationship between population and climate change; population size and composition have an impact on GHG emissions, whereas population dynamics (migration, fertility and death) are impacted by climate change (Ochi and Saidi, 2024). Population characteristics, including growth rates, must therefore be integrated into adaptation measures to effectively assess vulnerability and exposure to climate change. In addition to natural influences, human activity in the form of economic expansion is intrinsically linked to increased climate and environmental strains (Jakob et al., 2020). Understanding the relationship between GHG emission impacts and economic growth is thus important when devising strategies to offset the negative impacts of climate change and support sustainable development (Azzeddine et al., 2024).

To effectively reduce GHG emissions, it is imperative to recognize the socioeconomic aspects that contribute to climate change, as identifying these links will aid in developing GHG mitigation policies (Kuo et al., 2012; Ochi and Saidi, 2024). Dynamic modelling provides important baseline forecasts of energy demand and emissions trends by quantifying how socioeconomic variables influence future energy use. These outputs are then fed into mitigation models. Policymakers can prioritize mitigation efforts by utilizing dynamic modelling to identify sectors where drivers have the greatest impact on emissions; utilizing mitigation modelling tools is also key in creating effective data-driven Nationally Determined Contributions (NDCs) as it allows countries to make strategic choices that balance economic growth with climate action, ultimately contributing to global efforts to combat climate change (Hans et al., 2020).

Small Island Developing States (SIDS), like Trinidad and Tobago (T&T) have long been identified as among the world's most susceptible regions to climate change, experiencing sea-level rise, coastal erosion and extreme weather events (Morim et al., 2018; Vousdoukas et al., 2023). Due to its economy's reliance on fossil fuels, T&T was the 9th highest per capita emitter in 2023 (24.76tCO_2e), despite contributing only 0.1% of global GHG emissions (Government of the Republic of Trinidad and Tobago, 2022; Emissions Database for Global Atmospheric Research, 2024). This underscores the need for targeted climate action within the main contributing sectors. Following its commitments under the Paris Agreement (PA), T&T NDCs targets GHG emission reduction, from a business as usual (BAU) level, in the industrial, power generation and transportation by 15%, or 103 MtCO_2e, by the year 2030 (The Government of the Republic of Trinidad and Tobago, 2018; Ramsook et al., 2022; Ramsook et al., 2023).

Meeting these targets requires a thorough understanding of the drivers of energy consumption and associated GHG emissions. The absence of incorporating socioeconomic drivers in the development of T&T's NDCs limits their ability to reflect realistic and dynamic emission pathways; without incorporating GDP, population growth and sector-specific trends, projections of future GHG emissions risk being misaligned with actual demand patterns, making it more difficult to achieve the stated reduction targets. Understanding these links is crucial not just for improving the accuracy of GHG emission forecasting, but also for developing evidence-based mitigation policies that are tailored to suit the specific conditions and constraints of SIDS; prioritization of actions and resource allocations will also ensure that efforts are concentrated on sectors with the greatest potential for GHG reduction (Hans et al., 2020).

Despite growing global concern over GHG emissions, most existing case studies on GHG emission drivers focus on economies that overlook the unique structure and demographics of SIDS like T&T. Developing effective strategies for reducing climate change while maintaining sustainable economic growth requires understanding the intricate relationships between energy consumption and socioeconomic drivers. It is crucial to examine how socioeconomic factors interact with energy usage to improve fuel consumption forecasts and consequently related GHG emissions. This study addressed this gap for T&T by providing new insights into the relationships between population trends, economic activity and fuel consumption for two major sub-sectors, residential consumption and road transportation, which have emerged as critical areas owing to its continued reliance on fossil fuels such as diesel, gasoline, liquified natural gas (LPG) and natural gas-derived electricity. The findings were intended to evaluate the viability of current NDC targets as well as inform future NDC iterations and sector-specific mitigation policies aligned with sustainable development objectives.

This research aims to examine the dynamic relationship between key socioeconomic drivers, GDP obtained from World Bank Group (World Bank Group, 2025) and population obtained from the Central Statistical Office (CSO, 2023), against fuel consumption in T&T's residential consumption and road transportation sectors. The socioeconomic drivers, shown in Figure 1, present the historical trends of GDP and population for the assessment period 2000 to 2023, showing a general upward trajectory in economic output alongside a moderate population growth.

Figures 2-5 show a visual depiction of the historical data utilized for road transportation and residential energy consumption during the assessment period 2000 to 2023 (Ministry of Energy and Energy Industries, 2023). Diesel consumption, displayed in Figure 2, shows significant fluctuations in consumption, peaking around 2014 before declining in subsequent years. Gasoline consumption, Figure 3, shows a more stable upward trend in comparison to diesel with minor fluctuations. over the period, with notable declines in recent years.

For residential electricity consumption, Figure 4 demonstrates a consistent upward trajectory, a trend that closely parallels population growth. LPG consumption (Figure 5), however, showed a less consistent pattern with alternating periods of increase and decrease.

The study applied correlation analysis to measure and strength and direction of GDP and population against fuel consumption data and time series modelling to assess potential short-run and long-run linkages between these variables. Causal direction and the responsiveness of fuel consumption to changes in economic and demographic trends were also assessed. The findings aim to support more accurate GHG emissions forecasting and inform targeted, evidence-based mitigation strategies tailored to the national context of T&T as a SIDS.

2. LITERATURE REVIEW

Accurate projections for energy demand have become increasingly important in recent decades due to growing concerns about

Figure 1: Population and GDP historical data for Trinidad and Tobago for the period 2000-2023

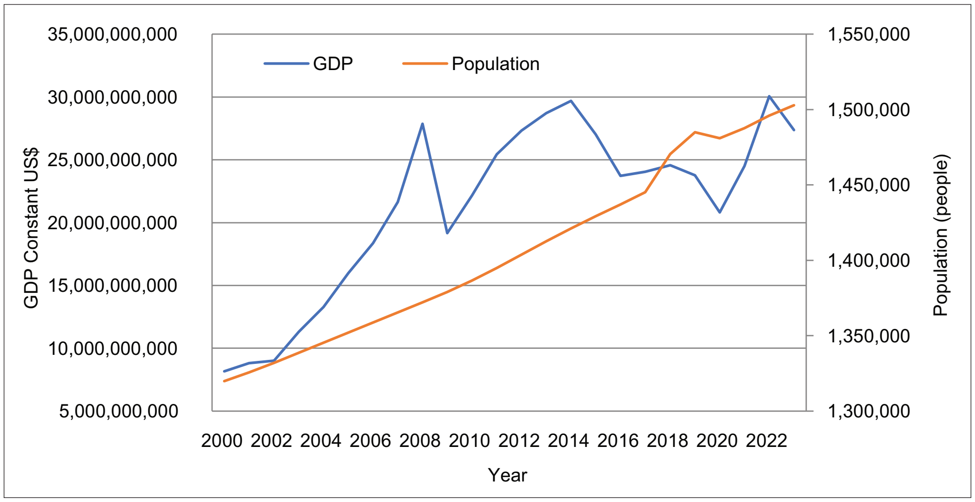


Figure 2: Diesel Consumption for Road Transportation in Trinidad and Tobago for the 2000-2023 period

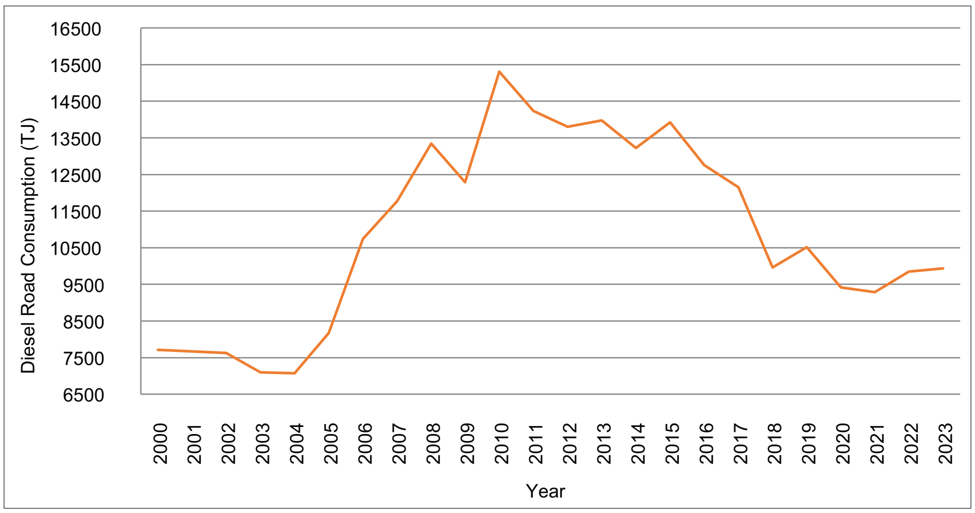
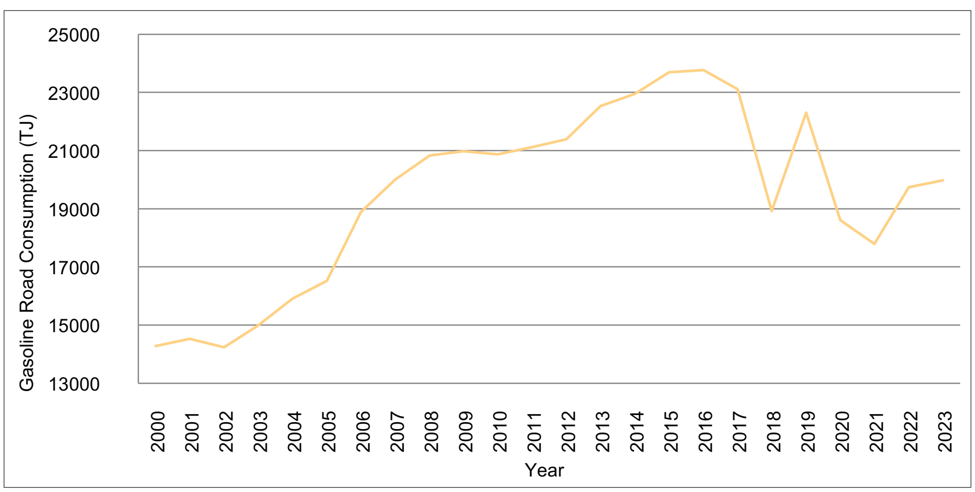


Figure 3: Gasoline Consumption for Road Transportation in Trinidad and Tobago for the 2000-2023 period



fossil fuel depletion and their associated rising GHG emissions (Suganthi and Samuel, 2012). These projections are needed to inform policymakers about future energy consumption trends, allowing for better supply system planning (Ghalehkhondabi et al., 2014). Forecasting approaches generally fall into two categories: causal or historical. Causal forecasting methods predict future outcomes by examining how a target variable responds to external drivers, such as economic, social and environmental factors, using tools like regression analysis and econometric modelling (Zhaozheng et al., 2010). In contrast,

Figure 4: Electricity Consumption for Residential Sector in Trinidad and Tobago for the 2000-2023 period

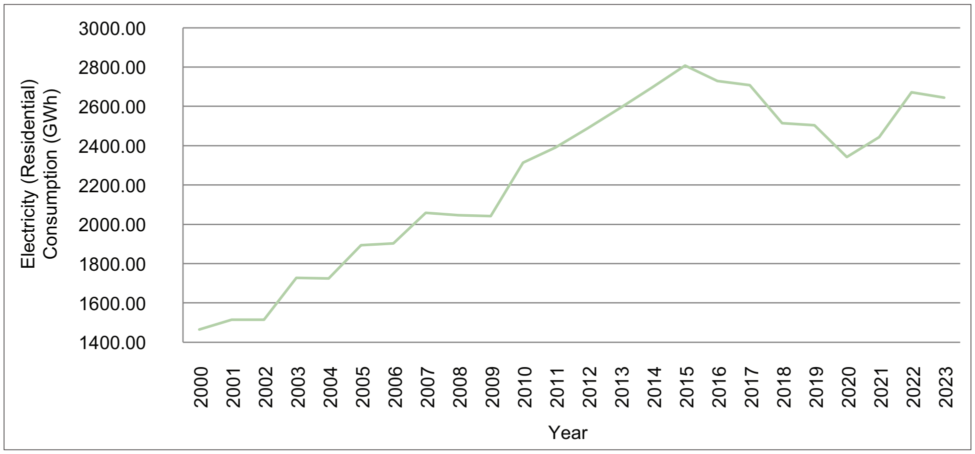
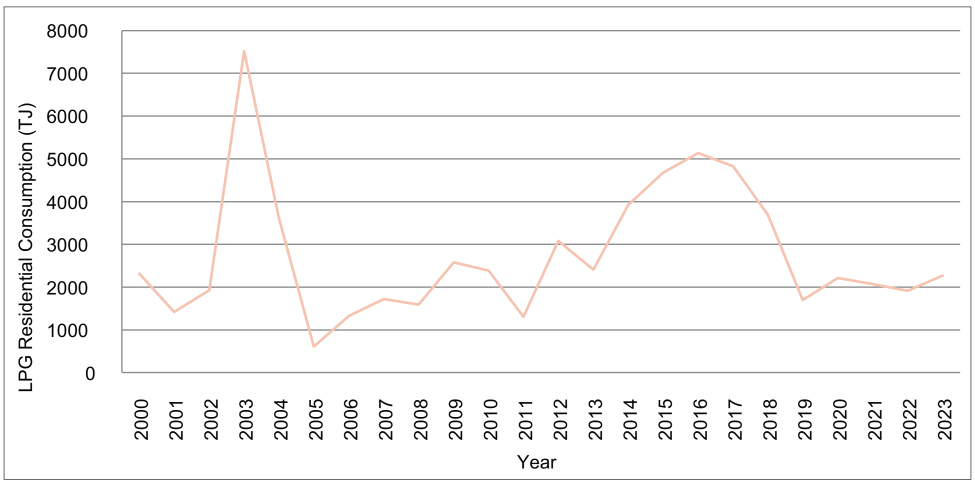


Figure 5: LPG Consumption for Residential Sector in Trinidad and Tobago for the 2000-2023 period



historical or time-based approaches rely solely on patterns within past data to project future values, employing techniques such as time series analysis, grey models and autoregressive methods (Hyndman and Athanasopoulos, 2021).

Accurately tracking the drivers and evolving patterns of anthropogenic emissions is essential for meaningful climate action. While understanding emission trends is crucial, effective mitigation of global warming ultimately depends on developing precise and reliable inventories of these human-induced emissions (Magazzino et al., 2024). According to Tavakoli (2018), identifying and evaluating sectoral contributions to emissions allows for more targeted and effective mitigation strategies. Through case studies that combine qualitative and quantitative data, the leading drivers of GHG emissions may be established; this data can then be extended to other nations with comparable characteristics (Streimikiene, 2022). According to researchers, the primary factors influencing anthropogenic GHG emissions were economic energy intensity, the reduction of energy consumption carbon intensity and economic growth, which were closely correlated with population expansion (Brodny and Tutak, 2021).

2.1. Correlation Analysis

Correlation analysis has been widely used in empirical energy and emissions research to assess the strength and direction of relationships between socioeconomic indicators and GHG emissions. Both Pearson's and Spearman's rank correlation offered valuable insight into these dynamics, which played an important part in identifying potential drivers of emissions prior to applying complex diagnostic modelling tools.

The Pearson correlation analysis was applied by Qin et al. (2023) to examine the linear relationships between CO_2 emissions and socioeconomic indicators, including GDP, population, energy consumption, renewable energy and energy intensity, across high-income and lower-middle-income countries from 1991 to 2021. Their findings revealed a positive correlation between energy consumption and emissions, with emphasis on developing countries, where economic and population growth enhanced fossil fuel demand; conversely, in developed countries, the increased energy efficiency moderated the relationship between GDP and emissions (Qin et al., 2023).

Similarly, in the 2023 study by Escamilla-Garcia et al. (2024), various socioeconomic factors and GHG emissions in Mexico were assessed using Pearson's correlation. The analysis revealed strong positive correlations between GHG emissions and variables such as GDP, population and energy consumption, suggesting that economic growth and demographic expansion were key drivers of emissions in this country. Conversely, factors like income inequality and educational attainment showed weaker or no significant correlations with emissions. These findings indicated that while economic and energy-related variables were closely tied to GHG outputs, social development indicators may not directly influence emissions patterns (Escamilla-Garcia et al., 2024).

While Pearson correlation has been a common tool in assessing linear relationships between socioeconomic variables and GHG emissions, Spearman correlation offers a robust alternative for capturing monotonic but potentially non-linear associations, particularly in cases where the data may not meet the assumptions of normality or linearity. In the study by Song et al. (2022), the Spearman correlation analysis was employed to examine the relationship between CO_2 emissions and land surface temperature (LST) from 2000 to 2017. The analysis revealed a significant positive correlation between total carbon emissions and LST, with Spearman coefficients ranging from 0.3 to 0.7 (Song et al., 2022). Their results highlighted that higher emissions regions also experienced increased surface warming. Tang et al. (2024) further applied the Spearman correlation analysis to examine the relationships between agricultural emissions and six key socioeconomic factors between 2000 to 2020 in Southwest China. Variables such as per capita rural income, mechanization and agricultural GDP showed statistically significant positive associations with GHG emissions, where the strength of these relationships varied by region, emphasizing the impact of localization in emission forecasting (Tang et al., 2024).

In a geographically grounded study, De Lotto et al. (2024) used both the Pearson and Spearman correlation methods to examine the relationship between land use and GHG. The goal of the study was to determine the direct correlations between GHG emissions in each municipality and demographic and territorial characteristics, such as road occupancy, land use patterns and population density. The researchers discovered that both correlation techniques demonstrated favorable relationships between GHG emissions and variables such as settlement extent and population density. The study did not explicitly compare the effectiveness of Pearson versus Spearman correlation analyses in their findings, instead, it emphasized the importance of integrating both statistical and spatial correlation techniques to gain a comprehensive understanding of the interplay between land use and emissions (De Lotto et al., 2024).

Given the complex nature and unpredictability of the relationships between GHG emissions in these sectors and income levels, population dynamics and energy consumption patterns, Spearman correlation offered a reliable statistical method for identifying significant links that linear approaches would overlook (Tang et al., 2024). Despite limited studies on the application of Pearson and Spearman correlation analysis to the road transport and residential consumption sectors, the above case studies affirmed the viability in capturing the influence of socioeconomic drivers on GHG emissions related to energy usage. By employing both correlation techniques, this study engaged in a comprehensive, preliminary analysis of the variables' interactions, serving as a foundation for subsequent dynamic modelling.

2.2 Diagnostic Modelling Analysis

Electricity consumption has been a central focus of energy-related studies due to its significance in both the industrial and residential sectors (Aydin, 2015; Cialani and Mortazavi, 2018; Wu et al., 2019). Globally, the residential sector accounted for approximately 30% of electricity use in 2017; this share is expected to remain substantial through 2040 (Lusis et al. 2017). The relationship between residential energy consumption and macroeconomic indices such as GDP and population has been extensively researched using Vector Autoregression (VAR) models and Vector Error Correction Model (VECM), which provided useful insights into both short and long run GHG emission trends.

Several studies have used the VAR model to assess the response of electricity consumption with changes in socioeconomic variables where the electricity demand was used as an independent variable influenced by driving factors, establishing a regression model to investigate the contribution of each influencing factor to electricity demand (Yu et al., 2017; Wang et al., 2018; Yang and Pang, 2021). Yang and Pang (2021), in particular, utilized unit root tests, Granger causality analysis, Johansen test and other co-integration analysis methods, to investigate the impact of urbanization, income levels and demographic growth on household power demand in China from 1995 to 2018. They discovered that GDP and urbanization rates Granger-caused power consumption, implying that economic growth and urban infrastructure expansion resulted in sustained increases in household energy demand. Their impulse response research also revealed that GDP shocks resulted in a considerable and sustained increase in power demand over a 3-5 year period, which was consistent with forecasts for developing economies experiencing rapid urbanization (Yang and Pang, 2021).

In Nigeria, Nathaniel and Bekun (2020) used a similar approach to examine the relationship between electricity consumption, urbanization and economic growth between 1971 to 2014. After confirming the stationarity of the first difference of the variables using proven unit root tests (Augmented Dickey-Fuller (ADF) and Phillips-Perron (PP)), long-run relationships between the variables were validated using cointegration tests. Their results also confirmed long-run relationships between electricity consumption, GDP and urbanization using unit root, cointegration and causality tests, highlighting bidirectional causality between electricity use and economic growth (Nathaniel and Bekun, 2020).

The macroeconomic policy of a country is heavily influenced by the type of relationship that exists between energy and economic growth. Several case studies have been conducted to develop econometric models to link energy consumption to GDP, however, there was a lack of sector-specific energy consumption data (Wolde-Rufael, 2006). Tatou et al. (2023) analysed the relationship between GDP and energy consumption in Morocco from 1997 to 2019, focusing on the residential, transportation and industrial sectors. To examine this causality, a VECM was used, as opposed to a VAR, with the Johansen cointegration approach. Their findings revealed that energy consumption by the transportation sector had a positive long-term influence on GDP, whereas residential consumption had a negative impact; in the short run, GDP was positively correlated with energy consumption by the industrial sector (Tatou et al., 2023).

In another case study by Karanfil and Li (2015), the short- and long-run dynamics of electricity consumption and economic activity were conducted using panel data from 160 countries, ranging from developed to developing nations, from 1980-2010. The study found a long-run cointegration relationship between electricity consumption and economic growth, using the VECM. They found stronger short-run causality in developed countries and more pronounced long-run relationships in developing nations, with results that were sensitive to regional and structural differences (Karanfil and Li, 2015).

Tamba (2020) investigated the association between LPG consumption and economic growth in Cameroon from 1975 to 2016 through unit root, cointegration and causality testing. Cointegration was accomplished using both the Johansen and autoregressive distributed lag limits approaches and causality was determined using the Granger test based on the VECM. The cointegration methods confirmed the presence of a level relationship, whereas the VECM causal tests revealed the existence of a short-run unidirectional causal relationship ranging from LPG consumption to economic growth, as well as a bidirectional causal relationship between long-term and high-causality variables. A positive association between LPG consumption and economic growth was concluded, implying that growth in the economy resulted in growth in LPG consumption (Tamba, 2020).

These findings emphasized that while residential energy consumption demand was influenced by economic and demographic factors, the strength and nature of these relationships vary across contexts, supporting the relevance of dynamic modelling approaches such as VAR and VECM in sector-specific energy analysis.

The road transportation sector plays a crucial role in national energy consumption and is a significant source of GHG emissions, especially in fossil-fuel-dependent economies. Fuel types such as diesel and gasoline dominate the transport energy mix in developing countries, making the sector a key target for climate mitigation. Several empirical studies have applied VAR and VECM to examine how transport fuel consumption and emissions are shaped by macroeconomic variables such as GDP, population growth, urbanization and fuel prices.

Meng and Han (2018) conducted a case study on CO_2 emissions associated with transport for Shanghai during the period 1989-2014. The causality relationships between these variables were investigated using Johansen cointegration, multivariate Granger causality tests based on VECM, impulse response functions and variance decomposition. Granger causality studies showed that road infrastructure expansion did not contribute to GDP growth in the transportation sector, but did result in a direct increase in transport CO_2 emissions; population density would result in lower CO_2 emissions per capita, according to the impulse response analysis (Meng and Han, 2018).

Xu and Lin (2015) also analysed the transportation sector in China and found that CO_2 emissions expanded by about 9.7 times between 1980 and 2012 (Xu and Lin, 2015). Identifying the causes of rising CO_2 emissions in the transportation sector became crucial for the implementation of successful environmental policy. Using VAR modelling, the factors that influence variations in CO_2 emissions in the industry were investigated. Their findings showed a correlation where energy efficiency significantly influenced the reduction of CO_2 emissions; urbanization also had a considerable impact on CO_2 emissions due to large-scale population movements and changes in the industrial structure. The impulse response functions demonstrated that economic shocks resulted in a positive, steady increase in the transport sector GHG emissions which would have peaked after 2-3 years (Xu and Lin, 2015).

In Tunisia, road transport was the primary source of CO_2 emissions from the transportation sector, which relied on fossil fuels. Talbi's (2017) study looked at the impact of gasoline consumption, road transport intensity, economic growth, urbanization and fuel rate on CO_2 emissions in Tunisia. The VAR model was used to investigate the factors that influenced changes in CO_2 emissions from Tunisia's transportation sector between 1980 and 2014. The results revealed that energy efficiency and fuel rate were the most important factors in lowering CO_2 emissions; the empirical findings verified the Environmental Kuznets Curve (EKC) hypothesis, which states that economic development in Tunisia follows an inverted U-shaped pattern in connection to CO_2 emissions (Talbi, 2017). The findings demonstrated that due to extensive population shifts and changes in the industrial structure, fuel rate and urbanization had a major impact on CO_2 emissions.

The examined research emphasized the context-dependent nature of the interaction between macroeconomic drivers and sectoral energy consumption. Yang and Pang (2021) and Xu and Lin (2015) studied how population growth and GDP variations affect household electricity demand and transportation fuel consumption, with varied degrees of short- and long-term effects across countries. Importantly, studies such as Tamba (2020) showed that even in resource-constrained situations such as Cameroon, economic growth could have a major impact on energy consumption patterns, particularly for fuels such as LPG, which were integrated into household energy use. While these studies provide useful insights, the majority were focused on large developing countries or regions, with limited application to SIDS like T&T. T&T presents a unique dynamic due to energy subsidies and low electricity tariffs and a high reliance on fossil fuels in the power generation and road transport (Regulated Industries Commission, 2021).

The reviewed literature underscores the relevance of both correlation analysis and time series modelling (VAR models and VECM) in understanding the short- and long-term dynamics between socioeconomic variables and GHG emissions across sectors. These methods are particularly useful for identifying causality, temporal impacts and context-dependent factors that drive emissions. Given T&T's unique context, marked by subsidized energy, low electricity tariffs and a high dependence on fossil fuels in residential and transportation sector, this study employed correlation analysis and time series modelling to investigate the dynamic relationships between GDP, population and energy consumption (diesel, gasoline, LPG and electricity) and their impact on GHG emissions in T&T's key sectors. It involved computing correlation coefficients to identify potential relationships between endogenous and exogenous variables, conducting stationarity tests, applying cointegration analysis to determine the proper model (VAR or VECM), building and validating the VAR/VECM model and performing Granger causality and impulse response analyses.

3. METHODOLOGY AND DATA

The methodology combined an analytical correlation analysis with a VAR modelling approach, accompanied by rigorous statistical tests at each step, as conducted in previous research. The overall process, outlined in Figure 6, was carried out using the EViews software platform.

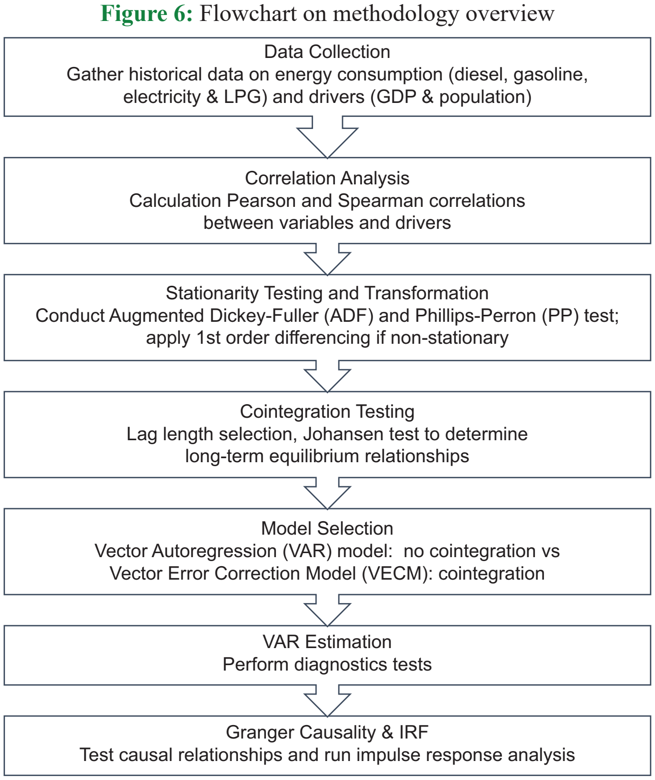
3.1. Analytic Correlation Analysis

Correlation analysis was first used to assess the strength and direction of association between the socioeconomic drivers (GDP and population) and energy consumption variables for the road transportation and residential power consumption variables. The Pearson's and Spearman's rank correlation coefficients were calculated, as in prior case of GHG emission drivers (Song et al., 2022; Ban et al., 2023; Qin et al., 2023; De Lotto et al., 2024; Li et al., 2024; Tang et al., 2024).

3.1.1. Pearson's correlation coefficient

The Pearson's correlation method, commonly used for normally distributed data, allows for the determination of the strength and direction of the relationship between two variables by calculating

Figure 6: Flowchart on methodology overview



a single quantitative measure (Thelwall, 2016). It measures the degrees of linear association between two variables, ranging from -1, having perfect negative linear correlation to +1, having perfect positive linear correlation (De Lotto et al., 2024). In this case study, the correlations between socioeconomic variables, GDP and population and fuel consumption were assessed separately.

Pearson's correlation between two matrices was calculated by adding the product of their differences from their respective means and dividing the result by the product of the squared differences from the mean (Eq. 1) (Asuero, et al., 2006).

$$r = \frac{\sum_{i=1}^{n}[(x_i - \bar{x})(y_i - \bar{y})]}{\sqrt{\sum_{i=1}^{n}(x_i - \bar{x})^2 \sum_{i=1}^{n}(y_i - \bar{y})^2}} \quad \text{(Eq. 1)}$$

Where *r* is the Pearson correlation coefficient, *x* and *y* (for example diesel against GDP) are the individual data points for the respective variables, $\bar{x}$ and $\bar{y}$ are the means of the variables, *i* is the index of each data point and n is the upper data point boundary (in this case study 23).

3.1.2. Spearman's correlation coefficient

Spearman's rank correlation coefficient, proposed by Spearman in 1904, is a non-parametric rank statistic established to assess the strength of an association between two variables by measuring the intensity and direction of a monotonic relationship, ideally of non-continuous data (Lehmann and D'Abrera, 2006). Spearman's correlation coefficient, calculated using (Eq. 2) (Gao, et al., 2023), has the advantage of being less sensitive to outliers than Pearson's correlation coefficient, which makes it suitable for data that is not normally distributed (Myers and Sirois, 2006). Spearman's rank correlation coefficients also range from -1 to +1, but it captures any monotonic relationship by evaluating how well the rank order of one variable predicts the rank of the other (De Lotto et al., 2024).

$$\rho = 1 - \frac{6\sum_{i=1}^{n} d_i^2}{n(n^2 - 1)} \quad \text{(Eq. 2)}$$

Where ρ is the Spearman correlation coefficient, d_i is the difference between the ranks of each paired variable for each data point (for example diesel against population), *i* is the index of each data point and n is the total number of data points (in this case study 23).

3.2. Test of Data Stationarity

Before estimating the multi-variable relationship, unit root tests were applied to each time series to determine their stationarity. Working with stationary data series is necessary as using non-stationary data to conduct regression analysis could produce inaccurate relationships (Greene, 2002). Box, Jenkins, Reinsel and Ljung (2016) further stated that using non-stationary data in regression could yield biased coefficients, resulting in invalid statistical inferences. Non-stationary time series could be transformed to attain stationarity, typically through first-order differencing (Eq. 3) (Lin et al., 2012; Xu and Moon, 2013; Xu and Lin, 2015; Guefano, et al., 2021). Using the ADF test along with PP as a confirmatory test, the null hypothesis that each series has a unit root, meaning it is non-stationary, was tested, as done in previous case studies (Xu and Lin, 2015; Jardon et al., 2017; Guefano et al., 2021).

$$\Delta y_t = y_t - y_{t-1} \quad \text{(Eq. 3)}$$

where Δy_t represents the first order difference, y_t is the current data; y_{t-1} is the previous year's data (for example LPG consumption (2001) – LGP consumption [2000]) and $t = 1, 2, \ldots T$ is the level time series (for this case study 23).

3.2.1. Augmented Dickey-Fuller (ADF) test

The ADF unit root test is one method of determining whether a time series was stationary or contained a unit root (Dickey and Fuller, 1979). This test has the capability to mitigate higher-order serial correlation by including a lagged difference term for the dependent variable (y_t) in the regression equation (Eq. 4) (Gujarati and Porter, 2022; Lin, et al., 2012). While ADF testing is commonly used in empirical studies, it has limitations due to its reliance on the OLS (ordinary least squares) method for linear model estimation; the low effectiveness of the ADF test was more prevalent for small sample sizes with strong autocorrelation; additionally, this approach was not suitable for testing stationary series with time trends (Xu and Lin, 2015).

$$\Delta y_t = \alpha + \beta t + \gamma y_{t-1} + \sum_{i=1}^{p} \delta_i \Delta y_{t-1} + \varepsilon_t \quad \text{(Eq. 4)}$$

where Δy_t the first difference of the series, α a constant, β_t the deterministic time trend, γ the coefficient of the lagged level of the series, δ_i coefficients for lagged differences, p the number of lagged difference terms and ε_t the error term.

3.2.2. Phillips-Perron (PP) test

While the PP test is based on the same regression framework as the ADF test, it offers greater robustness in the presence of heteroskedasticity and serial correlation in the residuals (Sabuhoro and Larue, 1997). Unlike the ADF test, which addresses autocorrelation by including lagged differences of the dependent variable, the PP test instead applies non-parametric corrections to the test statistic using Newey-West standard errors (Eq. 5) (Gujarati and Porter, 2022; Jardon, et al., 2017). This adjustment enhances the reliability of the test by accounting for autocorrelation and heteroskedasticity without increasing model complexity, thereby improving the accuracy of unit root detection under more flexible error structures.

$$\Delta y_t = \beta_0 + \alpha_0 t + \gamma_0 y_{t-1} + u_t \quad \text{(Eq. 5)}$$

where Δy_t the first difference of the series, α the intercept term, β_t the deterministic time trend, γ the coefficient of the lagged level of the series, u_i and the error term

3.3. Cointegration Testing

3.3.1. Lag Length Selection

An important step in VAR/VECM modelling is the selection of the optimal lag length for the model, as too few lags could omit relevant dynamics while too many lags could lead to a reduction in degrees of freedom and may overfit the sample (Eq. 6) (Xu & Lin, 2015). A balance between lag times and degrees of freedom must be achieved to obtain optimal results. The lag order was determined using minimizing standard information criteria, primarily the Akaike Information Criterion (AIC) (Eq. 7) (Xu & Lin, 2015) and Schwarz Criterion (SC) (Eq. 8) (Xu and Lin, 2015). The AIC was more likely to choose models with more lags because it penalized the number of parameters less severely to reduce the prediction error (Akaike, 1976); the SC, on the other hand, favored more economical models, especially in small samples, by imposing a greater penalty for model complexity (Schwarz, 1978; Gujarati and Porter, 2022).

$$AIC = -2\ln(\hat{L}) + 2k \quad \text{(Eq. 6)}$$

Where $\hat{L}$ is the maximized value of the likelihood function and k is the total number of estimated parameters in the model

$$SC = -2\ln(\hat{L}) + k\ln(n) \quad \text{(Eq. 7)}$$

where $\hat{L}$ is the maximized value of the likelihood function, n is the sample size, k is the total number of estimated parameters in the model and $ln(n)$ is the sample size dependent penalty term

Both tests were utilized and the lag length that sufficiently reflected the dynamics of the model without overfitting was selected.

3.3.2. Johansen cointegration test

After establishing that the series data were individually stationary in its first-order differential, the data were evaluated for cointegration to determine if any linear combinations of non-stationary level variables were also stationary. A stationary linear combination of non-stationary time series with unit roots is referred to as a cointegration equation, which represents a long-term equilibrium relationship between variables (Fan et al., 2021). The Engle-Granger two-step process (Engle and Granger, 1987) and Johansen-Juselius method (Johansen and Juselius, 1990; Johansen, 1995) were the most often used cointegration tests. The Engle-Granger two-step method is used for single equation cointegration tests, while the Johansen-Juselius method accurately determines the number of cointegration vectors. The Johansen cointegration test was used to find the number of cointegrating vectors in a multivariate system using the VAR model; this technique compared the null cointegrating relationships against alternatives using two statistics: trace and maximum eigenvalue (Engle and Granger, 1987). The Johansen test was essential for determining the appropriate model structure for multivariate time series analysis. If cointegration existed, it indicated a long-term equilibrium link between variables, such as comparing the impact of the socioeconomic variable against diesel; in this scenario, both short and long-run deviations would need to be considered by a VECM. A VAR model would be better suited for representing short-run variables in the absence of cointegration.

To ensure that the estimation technique matched the fundamental characteristics of the data and that conclusions about causal and dynamic linkages were statistically sound, the Johansen test functioned as a bridge for model selection between the stationarity analysis and the dynamic modelling methodology.

3.4. Dynamic Model

3.4.1. Vector autoregression (VAR) model

The VAR model involves numerous simultaneous equations where endogenous variables form a regression with lagged data to evaluate their dynamic relationships (Sims, 1980). The VAR model uses an unstructured technique to analyse multivariate time series variables and determine their statistical correlations where it is built by treating each endogenous variable as a function of their lagged values, estimating the dynamic relationships between joint endogenous variables without prior constraints (Eq. 8) (Hamilton, 1994; Fan et al., 2021).

$$y_t = A_1 y_{t-1} + \cdots + A_p y_{t-p} + B_0 x_t + B_1 x_{t-1} + \cdots + B_q x_{t-q} + \mu t \qquad \text{(Eq. 8)}$$

Where y_t is the endogenous variable in period t, A_p and B_q the corresponding coefficient matrices, x_t the dependent variables in the model, p and q the lag length order, μt the disturbance term.

For application to this study, an example is seen in Eq. 9:

$$\text{diesel}_{2022} = \text{A}_1\text{diesel}_{2001} + \text{A}_2\text{diesel}_{2000} + \text{B}_1\text{GDP}_{2001} + \text{B}_2\text{GDP}_{2000} + \text{B}_3\text{population}_{2001} + \text{B}_4\text{population}_{2000} + \mu_{2022} \qquad \text{(Eq. 9)}$$

Once stationarity was achieved and the lag length determined, the VAR models could be estimated using the ordinary least squares (OLS) method. Each coefficient in a VAR model represents the marginal impact, while holding other variables constant, of a one-unit change in a lagged variable on the current value of the dependent variable (Lutkepohl, 2005). As with OLS regression, P-values are analyzed for each coefficient in a VAR model to determine statistical significance; Lutkepohl (2005) indicated a P-value of less than 0.05 suggests strong evidence that the lagged variable has a statistically significant, non-random effect on the dependent variable. The VAR model validation process involved several tests, including data stationarity, lag order determination, variable exogeneity, model stability, cointegration, causality, impulse response and impact level analysis (Fan et al., 2021).

3.5. Granger Causality Analysis

Granger causality is a statistical concept used to assess whether one time series contains predictive information about another. According to Granger's framework, a variable X (e.g. GDP) is said to Granger cause another variable Y (e.g. gasoline consumption) if the past values of X significantly improved the prediction of Y, beyond what is possible using only past values of Y itself (Fomby et al., 2012). It is important to note that Granger causality reflects a predictive, not necessarily causal, relationship in the philosophical or structural sense; it simply indicates that historical values of one variable provide statistically significant information about the future behavior of another within the context of the model (Escamilla-Garcia et al., 2024).

3.6. Impulse Response Analysis

To quantify the dynamic impact of shocks, an impulse response function analysis was conducted. This methodology is essential for detecting shocks in all variables and quantifying the effects of those shocks, while explaining dynamic feedback among the various variables within the model (Xu and Lin, 2015). The impulse response function measures the changes in a system when a certain factor changes or fluctuates and traces out the effect of a one-time shock to one variable on the future values of other variables in the model. When a disturbance term varies during a period, it affects both the current and future values of the dependent variable due to system dynamics. Graphs are used to dynamically exhibit analyses, displaying the direction, magnitude and duration of the model's shock-related variables' responses across time; its benefit is that it highlights how variables change over time at the system level; for example, when the system as a whole experiences external shocks, it will become momentarily unstable but eventually adjust to achieve equilibrium (Guo et al., 2017).

This study took an econometric approach to analyzing the dynamic relationship between the socioeconomic variables and sector-specific fuel consumption in T&T. After confirming the stationarity of the variables using ADF and PP tests, optimal lag lengths were determined via the AIC and SC approach The Johansen cointegration test was then applied to assess short versus long-run equilibrium relationships, guiding the selection of the appropriate modelling framework. Granger causality testing was then used to identify directional predictive relationships among the variables and impulse response analysis was conducted to assess the magnitude and duration of shocks over time. The following sections present the results of these analyses.

4. RESULTS AND DISCUSSION

4.1. Analytic Correlation Analysis

The correlation analysis produced a matrix of coefficients for both the Pearson and Spearman correlations for each energy consumption variable against GDP and population. These results helped in identifying which driver had the strongest correlation with each exogenous variable. When looking at the Pearson correlation results (Table 1), the analysis revealed notable relationships between socioeconomic drivers and energy consumption. Residential electricity consumption exhibited a strong positive correlation with both GDP ($r \approx 0.93$) and population ($r \approx 0.86$), indicating that increased GDP and population growth were closely associated with higher electricity demand. Diesel and gasoline consumption, primarily associated with the road transportation sector, showed moderate to strong positive correlations with GDP ($r \approx 0.77$ and 0.88 respectively), while their correlation with population was weaker ($r \approx 0.33$ for diesel and 0.60 for gasoline). These findings imply that transport fuel consumption in T&T was more sensitive to changes in economic output than to demographic trends, likely due to the country's

Table 1: Pearson rank correlation coefficients between energy consumption fuels versus GDP and Population

Correlation	Diesel (TJ)	Gasoline (TJ)	Electricity (Residential) (TJ)	LPG (TJ)
GDP	0.773412	0.888330	0.929050	0.094273
Population	0.336014	0.598708	0.857982	0.179862

heavily industrialized, oil and gas economy. In contrast, LPG consumption demonstrated a weak and inconsistent correlation with both GDP (r ≈ 0.09) and population (r ≈ 0.18), suggesting that its use may be driven by additional factors not captured within the scope of this study.

The Pearson correlation analysis provided initial evidence of which socioeconomic variables were most strongly associated with different types of fuel consumption assessed. Unlike Pearson, which assumed linearity and normally distributed data, the Spearman test was non-parametric and more robust to non-linear relationships and outliers, making it particularly useful for time series data. The Spearman results shown in Table 2 revealed a strong positive correlation between residential electricity consumption and both socioeconomic variables (GDP (ρ ≈ 0.80) and population (ρ ≈ 0.83)), reaffirming the close alignment with increased consumption. Gasoline and diesel consumption also showed positive correlations with GDP (ρ ≈ 0.67 and ρ ≈ 0.63, respectively), though the strength was slightly lower than that observed in the Pearson analysis, indicating that the relationship may not be strictly linear; population had a weaker, though still positive, correlation with gasoline (ρ ≈ 0.53) and diesel (ρ ≈ 0.30) consumption. As with the Pearson test, LPG consumption exhibited low and inconsistent Spearman coefficients with both GDP (ρ ≈ 0.12) and population (ρ ≈ 0.18), suggesting a more complex or indirect relationship.

Overall, the Spearman analysis supported the findings of the Pearson test while accounting for potential non-linearities. It reinforced the conclusion that GDP and population were key drivers of electricity demand and, to a lesser extent, transport fuel use, offering a complementary statistical perspective that strengthens the validity of the results. These results combined helped justify the selection of variables for further dynamic modelling (Escamilla-Garcia et al., 2024; Li et al., 2024).

Table 2: Spearman rank correlation coefficients between energy consumption fuels versus GDP and Population.

Correlation	Diesel (TJ)	Gasoline (TJ)	Electricity (Residential) (GWh)	LPG (TJ)
GDP	0.633913	0.669565	0.801479	0.121739
Population	0.304348	0.526087	0.837139	0.176522

4.2. Test of Data Stationarity – Unit Root Test

4.2.1. Augmented Dickey-Fuller (ADF) test

The ADF test was performed for each variable (energy consumption fuels. GDP and population), which included the lags of the differenced series to account for autocorrelation. If the probability (P-value) obtained was greater than 0.05, the null of a unit root hypothesis must be accepted, indicating that the series was non-stationary. Table 3 showed that the original time series for residential electricity, gasoline, GDP and population had P-values above 0.05, signifying that the null hypothesis was accepted, indicating that the data equation was non-stationary except for diesel and LPG, which showed stationarity at level data. The ADF test was then applied to the first differences of each series; in the first differences, all variables had a $P < 0.05$, excluding diesel and population. The results showed that the majority of variables were non-stationary at level but became stationary after first differencing, indicating that they were integrated to the order one.

4.2.2. Phillips-Perron (PP) test

The PP test was also used as a robustness check to determine the stationarity of both the level and first-order differentials of the series data. The analysis of the PP results was consistent with the ADF testing in identifying the unit roots where a P-value below 0.05 would reject the null hypothesis and indicate a stationary state. In Table 4, $P > 0.05$ were observed for all level data, excluding LPG, indicating that a unit root exists. The PP results were generally consistent with the ADF test, with some minor discrepancies between the outcomes for diesel; sufficient evidence was found from previous studies to support the conclusion that the level series were of a non-stationary sequence despite the inconsistencies (Hondroyiannis, 2004; Peri and Baldi, 2010; Lin et al., 2012). The stationary test was then performed for the first-order difference. All first-order series data were found to be stationary, which allowed the co-integration test to be performed (Xu and Lin, 2015).

4.3. Cointegration Testing

4.3.1. Lag length selection

In time series modelling, choosing the right lag duration was crucial as it affected the ability of a model to capture the dynamic structure of the data without over-fitting. The optimal lag duration was determined via Logarithmic likelihood ratio (LogL), sequential modified LR test statistic (LR), Final

Table 3: Summary table unit root test: Augmented Dickey-Fuller (ADF)

Variable	ADF test statistics	Test critical values (t-statistics)			Probability (P)	Unit root test decision
		1% level	5% level	10% level		
Diesel	-4.027	-3.857	-3.040	-2.661	0.007	Stationary
D (Diesel)	-2.058	-3.788	-3.012	-2.646	0.262	Non-Stationary
Gasoline	-1.909	-3.753	-2.998	-2.639	0.323	Non-Stationary
D (Gasoline)	-5.951	-3.770	-3.005	-2.642	0.0001	Stationary
Electricity (Residential)	-1.661	-3.753	-2.998	-2.689	0.437	Non-Stationary
D (Electricity Residential)	-4.428	-3.770	-3.005	-2.642	0.002	Stationary
LPG	-3.145	-3.753	-2.998	-2.639	0.037	Stationary
D (LPG)	-5.251	-3.770	-3.005	-2.642	0.004	Stationary
GDP	-2.756	-3.770	-3.004	-2.642	0.331	Non-Stationary
D (GDP)	-2.711	-3.770	-3.004	-2.642	0.001	Stationary
Population	5.063	-3.857	-3.040	-2.660	1.00	Non-Stationary
D (Population)	1.163	-3.887	-3.052	-2.667	0.996	Non-stationary

Table 4: Summary table unit root test: Phillips-Perron (PP)

Variable	PP test statistics	Test critical values (t-statistics)			Probability (P)	Unit root test decision
		1% level	5% level	10% level		
Diesel	-1.522	-3.753	-2.998	-2.639	0.505	Non-stationary
D (Diesel)	-4.785	-3.770	-3.004	-2.642	0.001	Stationary
Gasoline	-1.909	-3.753	-2.998	-2.639	0.323	Non-stationary
D (Gasoline)	-5.939	-3.770	-3.004	-2.642	0.001	Stationary
Electricity (Residential)	-1.669	-3.753	-2.998	-2.639	0.4328	Non-stationary
D (Electricity Residential)	-4.461	-3.770	-3.005	-2.642	0.002	Stationary
LPG	-3.077	-3.753	-2.998	-2.639	0.047	Stationary
D (LPG)	-7.786	-3.770	-3.005	-2.642	0.000	Stationary
GDP	-2.527	-3.753	-2.998	-2.639	0.281	Non-stationary
D (GDP)	-2.672	-3.770	-3.005	-2.642	0.001	Stationary
Population	0.128	-3.753	-2.998	-2.639	0.961	Non-stationary
D (Population)	-3.367	-3.770	-3.005	-2.642	0.024	Stationary

Table 5: Criteria to select lag length for independent variables

Variable	Lag	LR	FPE	AIC	SC	HQ
Diesel	0	NA	1.83exp+38	99.45199	99.65036	99.49872
	1	181.5474	1.86 exp+34	90.22728	91.21913*	90.46093
	2	27.94304*	1.10 exp+34*	89.53236*	91.31770	89.95293*
Gasoline	0	NA	3.35 exp+34	88.00988	88.15866	88.04492
	1	144.7286	2.47 exp+31	80.78758	81.38270*	80.92777
	2	18.77654*	1.70 exp+31*	80.35400*	81.39545	80.59933*
Electricity (Residential)	0	NA	4.59 exp+32	83.71990	83.86868	83.75495
	1	146.5398*	3.07 exp+29*	76.39699*	76.99210*	76.53718*
	2	9.083704	4.01e+29	76.60959	77.65104	76.85492
LPG	0	NA	9.08e+34	89.00789	89.15667	89.04293
	1	141.6033*	7.99e+31*	81.95922*	82.55433*	82.09941*
		6.958855	1.20e+32	82.31348	83.35493	82.55881

LR: Sequential modified LR test statistic (each test at 5% level), FPE: Final prediction error, AIC: Akaike information criterion, SC: Schwarz information criterion, HQ: Hannan-Quinn information criterion

prediction error (FPE), Akaike information criterion (AIC), Schwarz information criterion (SC) and Hannan-Quinn (HQ) information criterion. Table 5 displays the results of the models with varied lag orders. The models were investigated and the lag probability with the lowest value was selected as the optimum lag length for each criterion. The most favourable lag for diesel and gasoline was lag 2 for the AIC, FPE, HQ and LR criterion, while the SC recommended lag 1; given the small sample size (annual date between 2000 to 2023), SC was typically preferred for simplicity, however as the dynamics of the models were significant, the lag 2 would offer better predictions and selected as the preferred option. For both residential electricity consumption and LPG, strong agreement across all criteria suggested lag 1 as the optimal choice.

While unit root tests (ADF and PP) confirmed that the series were integrated of order one, this does not automatically imply cointegration. The optimum lag selections were then incorporated in the cointegration test to determine whether a long-run equilibrium relationship exists among the variables in the study.

4.3.2. Johansen cointegration test

The Johansen cointegration test was used to determine whether a long-run relationship exists among the non-stationary variables—GDP, population and fuel consumption. The null hypothesis was rejected at a critical value of 0.05, indicating a co-integration relationship. If the variables were cointegrated, a VAR model with an error correction factor (VECM) should be employed; otherwise, the VAR model should be utilized (Kuo et al., 2012). A summary of the results obtained was presented in Table 6.

Table 6: Johansen co-integration test results

Endogenous variable	Number of co-integration relationships	Trace statistics	5% Critical value	Probability (P)
Diesel	None	24.12126	29.79707	0.1954
	At most 1	9.017160	15.49471	0.3638
	At most 2	1.339902	3.841465	0.2471
Gasoline	None	27.50592	29.79707	0.0898
	At most 1	5.589654	15.49471	0.7434
		0.519480	3.841465	0.4711
Electricity (Residential)	None	25.95974	29.79707	0.1299
	At most 1	12.45656	15.49471	0.1363
	At most 2	1.796906	3.841465	0.1801
LPG	None	21.60932	29.79707	0.3207
	At most 1	5.139574	15.49471	0.7938
	At most 2	0.580480	3.841465	0.4461

The analysis found no significant cointegration between energy consumption fuels and the two driving variables, GDP and population at 5%, indicating no long-term equilibrium relationship. Looking at the diesel model as a reference, the trace test suggested no cointegrating vectors, implying that the diesel consumption for road transportation does not have a stable proportional relationship with GDP and population in the long run for the assessment period. While all variables were found to be integrated of order one, the test confirmed that they were not cointegrated. This result justified the use of a VAR model in first differences rather than a VECM, ensuring the analysis focused on valid short-run dynamics and avoided spurious results.

4.4. Vector Autoregression (VAR) Analysis

The VAR models were developed where each fuel consumption variable was treated as endogenous and regressed against its lag as well as the lagged values of both GDP and population (optimum lag length established in the previous section) (Table 7), where coefficients were considered significant with $P < 0.05$. Diesel consumption was significantly influenced by its lagged value and GDP, with a two-period lag, indicating that economic activity had a delayed but measurable impact on diesel demand. Gasoline consumption also showed a statistically significant, positive response to GDP lag by one year, suggesting that private transport fuel usage may be closely linked to short-term economic fluctuations. In contrast, residential electricity consumption was primarily driven by its past values, reflecting strong resistance to change and stable usage patterns over time, with no statistically significant short-run influence from GDP or population. LPG consumption exhibited weak dependence on its lag and no significant relationship with either socioeconomic variable. Across the models, population does not emerge as a statistically significant short-run driver in any of the equations, although its influence may still manifest over longer time horizons. Overall, the coefficients highlight the importance of economic output, particularly GDP, as a key short-term determinant of transport-related energy demand in T&T, while electricity and LPG appeared less immediately responsive to socioeconomic shifts.

Building on the results of the VAR models, further analysis was required to determine the direction of influence between these variables. While the VAR framework identified temporal dependencies, it does not establish whether changes in GDP or population precede and predict changes in energy consumption. The Granger causality test was applied, which assessed whether

Table 7: VAR models for energy consumption variables against driver variables

Endogenous Variable	VAR Model	Coefficients	Probability (P)
Diesel	DIESEL=C (1) *DIESEL(-1) + C (2)	C (1) 0.572266	0.0408
	*DIESEL(-2) + C (3) *GDP(-1) + C (4)	C (2) -0.16803	0.5229
	*GDP(-2) + C (5) *POPULATION(-1) + C (6)	C (3) 3.53 exp-08	0.7266
	*POPULATION(-2) + C (7)	C (4) 2.49 exp-07	0.0297
		C (5) -0.00842	0.8786
		C (6) -0.01264	0.8173
		C (7) 30801.37	0.0076
Gasoline	GASOLINE=C (1) *GASOLINE(-1) + C (2)	C (1) -0.09512	0.6677
	*GASOLINE(-2) + C (3) *GDP(-1) + C (4)	C (2) 0.17603	0.3121
	*GDP(-2) + C (5) *POPULATION(-1) + C (6)	C (3) 2.66 exp-07	0.0025
	*POPULATION(-2) + C (7)	C (4) 2.09 exp-07	0.0881
		C (5) 0.070183	0.1761
		C (6) -0.09138	0.0790
		C (7) 37821.03	0.0001
Electricity (Residential)	ELECTRICITY_RESIDENTIAL=C (1)	C (1) 0.747072	0.000
	*ELECTRICITY_RESIDENTIAL(-1)	C (2) 9.32 exp-09	0.2629
	+ C (2) *GDP_CURRENT(-1) + C (3)	C (3) 2.06 exp-04	0.7720
	*POPULATION+C (4)	C (4) 1.22 exp+02	0.8810
LPG	LPG=C (1) *LPG(-1) + C (2) *GDP_	C (1) 0.368259	0.0902
	CURRENT(-1) + C (3)	C (2) 4.12 exp-08	0.5698
	*POPULATION(-1) + C (4)	C (3) -3.31 exp-03	0.6697
		C (4) 5.61 exp+03	0.5735

Table 8: Granger causality test results and conclusions

Null hypothesis	F statistics	Probability (P)	Conclusion
GDP does not Granger Cause Diesel	0.47582	0.6294	Accept
Diesel does not Granger Cause GDP	0.09318	0.9115	Accept
Population does not Granger Cause Diesel	0.66104	0.5291	Accept
Diesel does not Granger Cause Population	2.03588	0.1612	Accept
GDP does not Granger Cause Gasoline	2.59185	0.1041	Accept
Gasoline does not Granger Cause GDP	0.35818	0.7041	Accept
Population does not Granger Cause Gasoline	1.16563	0.3354	Accept
Gasoline does not Granger Cause Population	7.03979	0.0059	Reject
GDP does not Granger Cause Electricity (Residential)	1.26904	0.2733	Accept
Electricity (Residential) does not Granger Cause GDP	0.71526	0.4077	Accept
Population does not Granger Cause Electricity (Residential)	0.01677	0.8983	Accept
Electricity (Residential) does not Granger Cause Population	4.38649	0.0492	Reject
GDP does not Granger Cause LPG	0.14919	0.7034	Accept
LPG does not Granger Cause GDP	0.17571	0.6796	Accept
Population does not Granger Cause LPG	0.00019	0.9892	Accept
LPG does not Granger Cause Population	3.12973	0.0921	Accept

past values of one variable could statistically improve the prediction of another. This test was essential for understanding causal relationships and provided valuable insights into which drivers were most influential in shaping energy demand across sectors.

4.5. Granger Causality Analysis

For each pair of energy consumption variables versus the driver variables, for example, GDP versus diesel consumption, the null hypotheses were set, which would state GDP does not Granger cause diesel consumption (Table 8). If the P < 5%, the null hypothesis was rejected, indicating a Granger causality in that direction. In the road transport fuel models, GDP nor population showed any statistically significant Granger causality on both diesel and gasoline consumption. This suggested that changes in road transportation fuel use and changes in macroeconomic indicators occurred concurrently without a clear predictive lead-lag behavior for the sample period; no significant Granger causality was also detected between LPG consumption and the driver variables. For residential electricity consumption, a weak positive Granger causal effect was noted from the population driver, which may indicate a common trend between both variables.

The lack of Granger causality implied that, in historical data, changes in one variable did not systematically predict changes in the other. Overall, the results showed that while GDP had a contemporaneous relationship with energy use, it did not predict short-term changes in energy consumption. Population changes were gradual, resulting in minimal short-run causation; nevertheless, in the electricity model, some effect was identified, possibly due to population expansion directly increasing residential electricity demand.

The Granger causality test investigated which of the variables influenced the other, hence determining the causal relationship between variables; it was frequently used to determine if a variable may be utilized to increase the prediction power of other variables in a VAR model (Fan et al., 2021). While the Granger causality tests identify the existence and direction of predictive relationships between these socioeconomic drivers and fuel consumption, they do not reveal the magnitude or duration of these effects over time. To better understand how energy consumption variables respond to shocks in GDP and population, impulse response analysis was conducted. The following section presents and interprets these impulse response results, offering deeper insight into the temporal effects of socioeconomic drivers on energy demand in T&T.

4.6. Impulse Response Analysis

An impulse response function was developed to study the impact of GDP and population changes in the VAR model on consumption variables. For example, if GDP experienced an unanticipated shock in a given year, how would it affect diesel consumption in later years? The impulse response produced a time profile of diesel's response, including the immediate impact and duration of impacts, with all other shocks set to zero. Figures 7-10 show the comparable figures. The impulse response function is represented as a solid line, with a dashed range indicating changes within twice the standard deviation.

It was observed that a positive GDP shock increased energy consumption in both the road transportation and residential sectors, peaking at 1-2 years. A positive GDP shock caused a temporary boost in diesel and gasoline consumption, but the effect faded within 2-3 years, returning to the baseline shown in Figures 7a and 8a. This showed that transport energy responses to economic variations were short-lived, possibly due to the dominance of private vehicles over public transportation in T&T, as opposed to more industrialized economies where GDP shocks had long-term effects on logistics and freight fuel consumption (Xu and Lin, 2015). Diesel consumption responded to a population

Figure 7: Response of (a) Diesel to GDP Innovation (b) Diesel to population Innovation

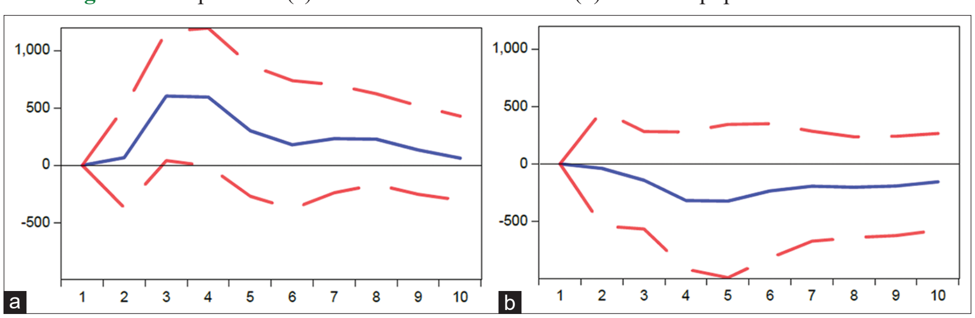


Figure 8: Response of (a) Gasoline to GDP Innovation (b) Gasoline to population Innovation

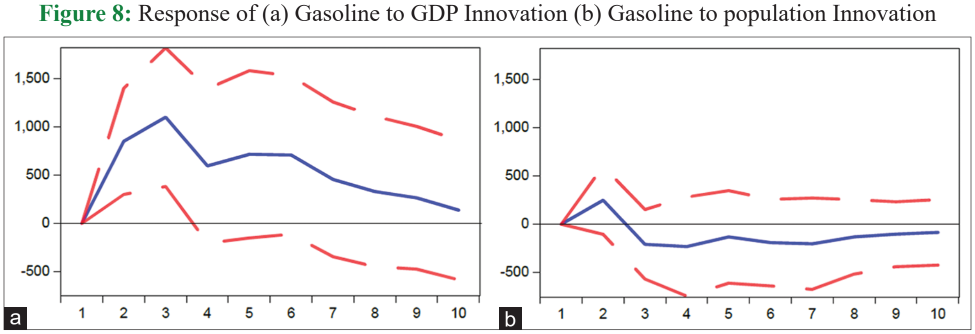


Figure 9: Response of (a) Electricity (Residential) to GDP Innovation (b) Electricity (Residential) to population Innovation

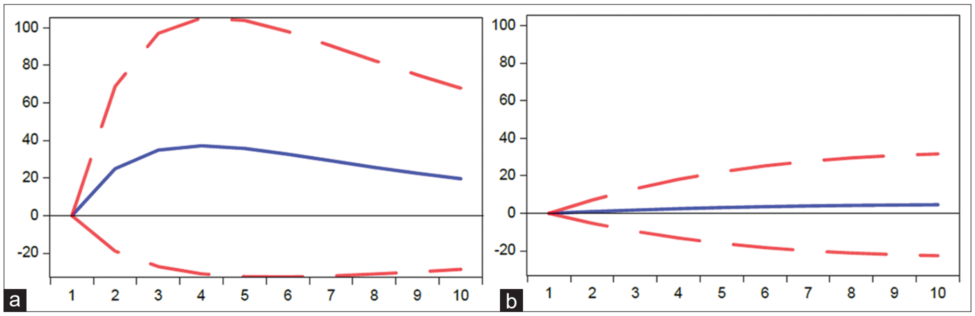
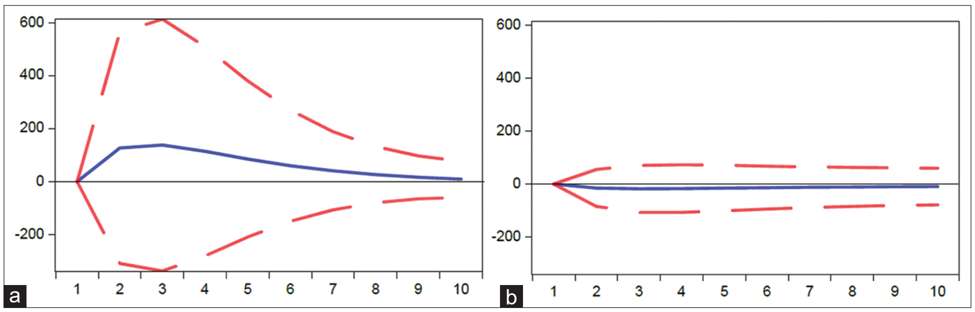


Figure 10: Response of (a) LPG to GDP Innovation (b) LPG to population Innovation



shock in a subdued and minor manner across the periods, Figure 7b. This showed that population growth had no impact on diesel consumption in the short or long run, possibly indicating a very inelastic transport fuel demand structure. However, population shocks resulted in a long-term increase in gasoline usage as shown in Figure 8b. The reaction increased gradually, from periods 1 to 5. This suggested that population expansion had a more consistent long-term impact on gasoline demand in road transport, which could be attributed to greater private vehicle usage or urbanization.

A GDP shock resulted in a noticeable and continuous increase in residential electricity consumption, which peaked between periods 2 and 3 before settling at a higher level than the baseline (Figure 9a); the persistent impact revealed that economic expansion had a beneficial influence on residential electricity demand. In contrast, LPG consumption showed a slight and short-lived positive response to GDP shocks, Figure 10a, peaking around period 1 and quickly returning to baseline. The small effect implied that GDP growth had no substantial impact on LPG consumption. Population shocks caused a modest but constant increase in electricity use (Figure 9b). The response was more sustained and cumulative, demonstrating that population growth had a direct and long-term impact on household electricity consumption. This was consistent with the expectation that a rising population would lead to more households and, consequently, higher electricity demand over time. The response to a population shock was minimal and statistically insignificant for LPG consumption seen in Figure 10b. This revealed that population dynamics have no substantial impact on LPG consumption in the residential sector.

Overall, the results from the VAR modelling, Granger causality tests and impulse response analysis provided a comprehensive view of the short-run dynamics between socioeconomic drivers and fuel consumption in T&T. While GDP exhibited limited influence across most energy types, population growth emerged as a more consistent and significant driver particularly for residential electricity and gasoline consumption. These findings underscore the importance of demographic trends in shaping future energy demand and emissions patterns.

5. CONCLUSION

This study investigated the short-run dynamics between key socioeconomic drivers, GDP and population and fuel consumption in T&T's residential consumption and road transportation sector using a VAR approach. The analysis was guided by rigorous statistical testing, including correction analysis, unit root tests, cointegration assessments, Granger causality testing and impulse response functions.

The correlation analysis revealed that GDP and population were significantly associated with electricity consumption, showing strong positive Pearson and Spearman coefficients (GDP: $r \approx 0.93$ and $\rho \approx 0.80$ and population: $r \approx 0.80$ and $\rho \approx 0.84$), which indicated that increases in these drivers were aligned with higher residential electricity demand. Road transportation fuels, diesel and gasoline, also showed positive associations with GDP (r and ρ values > 0.60), but weaker correlations with population (within a 0.3 to 0.6 range for r and ρ values), particularly for diesel consumption.

The unit root tests (ADF and PP) both confirmed that the majority of the time series were non-stationary at level (>0.05 accepting null hypothesis) but stationary at first difference (<0.05 rejecting null hypothesis). Cointegration testing using the Johansen method found no evidence of long-run relationships among the socioeconomic drivers and the energy consumption variables;

these tests were conducted on the optimum lag length selection (lag 1 for residential electricity and LPG and lag 2 for diesel and gasoline consumption) for each model using the AIC and SS tests. This meant that, while GDP and population had an immediate impact on energy consumption, these factors do not move in conjunction over time. As a result, a VAR model rather than a VECM was employed to explore short-run dynamics.

The VAR model coefficients demonstrated that while electricity and LPG were less responsive to socioeconomic changes, GDP was a significant short-term predictor of transport-related energy demand.

Granger causality tests further supported these insights, showing no statistically significant causality between GDP or population and diesel or LPG consumption, reinforcing the finding that these fuels exhibit minimal short-run responsiveness to macroeconomic fluctuations. However, a unidirectional Granger causal relationship was detected from residential electricity consumption to population.

The impulse response functions confirmed these dynamics, where shocks to GDP had short-term impacts on diesel and gasoline demand, peaking within 1–2 years and then dissipating. In contrast, population shocks led to a gradual and sustained increase in gasoline consumption, indicating a long-term linkage between demographic trends and road fuel demand. Residential electricity consumption responded positively and persistently to both GDP and population shocks.

Overall, the results suggested that population growth was a more consistent and influential driver of energy consumption, especially for residential electricity and gasoline, compared to GDP in the short run. By introducing a data-driven approach to examining the dynamic interplay between socioeconomic drivers and sector-specific fuel consumption, this study enhances the accuracy of fuel use and GHG emissions projections. These improved forecasts can inform the development of more targeted and effective mitigation strategies. In doing so, the findings contribute to building a stronger empirical foundation for future iterations of T&T's NDCs, promoting a shift from broad, generic targets to more precise, evidence-based mitigation pathways that align with the country's unique economic and demographic context.

By showing the value of integrating correlation analysis with VAR modelling to investigate short-term interdependencies between socioeconomic variables and sectoral energy demand, this work makes a methodological contribution that goes beyond the national setting. This integrated, data-driven approach facilitates more accurate energy and emissions forecasting and offers a rigorous foundation for the development of empirically grounded mitigation policies. The development of context-specific, evidence-based NDCs can be aided by the replication of this method across SIDS, given the shared reliance on fossil fuels, vulnerability to fluctuations in energy prices and limitations in data availability. This will allow these nations to move from fixed carbon reduction goals to more flexible, sector-specific approaches tailored to their socioeconomic trends.

6. RECOMMENDATION FOR FUTURE WORK

To improve the precision of fuel consumption estimates, strengthen mitigation scenario planning and facilitate the advancement of T&T's climate commitments under its NDCs, several directions for further research and policy development are suggested in light of the study's findings:

6.1. Develop Forecasting Models for Fuel Consumption

To improve the accuracy of national GHG emission projections, future research should build on the VAR framework used in this study by developing extended, sector-specific forecasting models. These models should simulate fuel consumption trends under several economic and demographic scenarios, using the empirical relationships identified as a foundation for the development of BAU projections. By projecting future energy demand more precisely, particularly in the residential consumption and transportation sectors, such research will better inform estimates of associated GHG emissions and support more effective, data-driven climate policy planning.

6.2. Create Scenarios for Mitigation by Employing Sensitivity Analysis

Sensitivity analysis should be used in future studies to create mitigation scenarios that evaluate the effects of changes in population, GDP and other important factors on fuel consumption and GHG emissions. This will help identify the most influential variables and support the design of flexible, data-driven mitigation strategies that can adapt to different future development pathways. By applying sensitivity analysis to explore how changes in socioeconomic drivers affect fuel consumption and emissions, future research can generate a range of realistic mitigation scenarios.

6.3. Assess Viability of Achieving Current NDC Goals and Improve the Development of Future NDCs

Future studies should compare T&T's present NDC targets with empirically generated fuel consumption and emissions predictions to determine whether they are attainable. This will help identify any gaps between actual trends and pledged reductions. Additionally, incorporating these findings into future NDC development will enable the creation of realistic, sector-specific and data-driven targets, improving the effectiveness and credibility of national climate commitments.

6.4. Build and Maintain National Emissions Databases

To support ongoing modelling and planning, it is recommended that T&T invest in a centralized, regularly updated database of energy consumption and GHG emissions by sector, fuel type and other sub-sectors. This will enhance transparency, monitoring and policy responsiveness.

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