CPD

Working Paper 153

The Future Unplugged

Forecasting a Comprehensive Energy Demand of Bangladesh - a Long Run Error Correction Model

Khondaker Golam Moazzem
Faisal Quaiyyum

CENTRE FOR POLICY DIALOGUE

THE FUTURE UNPLUGGED

Forecasting a Comprehensive Energy Demand of Bangladesh - a Long Run Error Correction Model

CPD Working Paper 153

Khondaker Golam Moazzem
Faisal Quaiyyum

Published in April 2024

Centre for Policy Dialogue (CPD)
House 40/C, Road 11 (new)
Dhanmondi, Dhaka-1209, Bangladesh
Telephone: (+88 02) 55001185, 55001990, 58156983
Fax: (+88 02) 48110414
E-mail: info@cpd.org.bd
Website: www.cpd.org.bd

Disclaimer: The views expressed in this paper are those of the authors alone and do not necessarily reflect the views of CPD.

Citation: Moazzem, K. G., and Quaiyyum, F. (2024). *The Future Unplugged: Forecasting a Comprehensive Energy Demand of Bangladesh - a Long Run Error Correction Model*. CPD Working Paper 153. Centre for Policy Dialogue (CPD).

ISSN 2225-8175 (Online)

The **Centre for Policy Dialogue (CPD)** was established in 1993 as a civil society initiative to promote an ongoing dialogue between the principle partners in the decision-making and implementing process. Over the past 30 years, the Centre has emerged as a globally reputed independent think tank, with local roots and global reach.

A key area of CPD's activism is to organise dialogues to address developmental policy issues that are critical to national, regional and global interests, with a view to seeking constructive solutions from major stakeholders. The other key area of CPD's activities is to undertake research programmes on current and strategic issues.

CPD's research programmes are both serviced by and intended to serve, as inputs for particular dialogues organised by the Centre throughout the year. Major research themes are: macroeconomic performance analysis; poverty and inequality; agriculture; trade; regional cooperation and global integration; infrastructure; employment, and enterprise development; climate change and environment; development governance; policies and institutions; and the 2030 Agenda for Sustainable Development.

As a continuation of its work, CPD has collaborated with various eminent networks, i.e., World Economic Forum (WEF), South Asia Economic Summit (SAES), Bangladesh, China, India and Myanmar (BCIM) Forum, South Asia Centre for Policy Studies (SACEPS), etc. CPD hosts the secretariat of the *LDC IV Monitor*, an independent global partnership for monitoring the outcome of the Fourth UN Conference on the LDCs. CPD was also the initial convener and founding host of the Southern Voice on Post-MDGs, a network of 50 think tanks from Africa, Asia and Latin America. CPD was the Secretariat of Southern Voice during January 2013–June 2019. At the national level, CPD hosts the Secretariat of the *Citizen's Platform for SDGs, Bangladesh*, a civil society initiative that includes more than 100 Partner organisations, founded with an objective to contribute to the delivery and implementation of the Sustainable Development Goals (SDGs). In recognition of its track record in research, dialogue and policy influencing, CPD has been selected as an awardee of the Think Tank Initiative (TTI) for two consecutive terms.

Dissemination of information and knowledge on critical developmental issues is another important component of CPD's activities. Pursuant to this, CPD maintains an active publication programme, both in Bangla and in English. As part of its dissemination programme, CPD has been bringing out **CPD Working Paper Series** on a regular basis. Research work in progress, background papers of dialogues, investigative reports and results of perception surveys which relate to issues of high public interest are published under this series.

The present paper titled ***The Future Unplugged: Forecasting a Comprehensive Energy Demand of Bangladesh - a Long Run Error Correction Model*** has been prepared by *Dr Khondaker Golam Moazzem*, Research Director, CPD (moazzem@cpd.org.bd); and *Mr Faisal Quaiyyum*, Programme Associate, CPD (faisal@cpd.org.bd).

Series Editor: *Dr Fahmida Khatun*, Executive Director, CPD.

Abstract

In this study, we critically evaluate Bangladesh's energy forecasting framework, pinpointing gaps in the Integrated Energy and Power Master Plan (IEPMP) and introducing an advanced econometric approach through the Vector Error Correction Model (VECM). By integrating environmental considerations with economic and demographic factors, we propose a multidimensional framework that not only addresses current energy challenges but also anticipates future shifts in consumption patterns. This approach paves the way for a holistic energy strategy that balances growth with sustainability. Our analysis uncovers a more realistic energy consumption trajectory up to 2050, significantly diverging from the IEPMP's projections which anticipate 3.75 times increase by 2050. In stark contrast, our scenarios forecast a more tempered growth, ranging from 1.7 to 2.36 times. Similarly, for 2041, where IEPMP envisions a 2.6 times growth, our models suggest a more modest increase between 1.51 to 1.88 times. By 2030, against IEPMP's projection of 1.68 times, our findings present a range from 1.24 to 1.37 times. This utter discrepancy underscores the need for methodological refinement and policy recalibration, and adjustment of renewable energy targets, ensuring future energy strategies are both sustainable and aligned with empirical evidence.

Acknowledgements

The study was conducted under the CPD Power and Energy Unit. The research team would like to thankfully acknowledge the continuous and rigorous feedback of the modelling from *Mr Sayed Jubair bin Hossain*, Lecturer, Department of Economics, University of Dhaka.

The authors also express their sincerest acknowledgement and appreciation to *Mr Avra Bhattacharjee*, Joint Director of Dialogue and Outreach at CPD, for his valuable support. Additionally, the team would like to thank *Mr HM Al Imran Khan*, Publication Associate, CPD, for his contribution in shaping, refining, and finalisation of the manuscript.

Table of Contents

List of Tables

Acronyms

ADF	Augmented Dickey Fuller
AGO	Accumulated Generating Operations
AIC	Akaike Information Criterion
ANN	Artificial Neural Network
ARMA	Autoregressive Moving Average
ATS	Advanced Technology Scenario
BAU	Business As Usual
BCVTB	Building Control Virtual Test Bed
GA	Genetic Algorithm
GDP	Gross Domestic Product
GoB	Government of Bangladesh
GPRM	Gary Prediction with Rolling Mechanism
HQC	Hannan–Quinn Information Criterion
IEPMP	Integrated Energy and Power Master Plan
IMF	International Monetary Fund
JICA	Japan International Cooperation Agency
LEAP	Long-range Energy Alternative Planning
MLR	Multiple Linear Regression
MoPMER	Ministry of Power, Energy and Mineral Resource
Mtoe	Millions of Tonnes Oil Equivalent
OWID	Our World in Data
PSO	Particle Swarm Optimization
SBIC	Schwarz Bayesian Information Criterion
SSA	Singular Spectrum Analysis
SVR	Support Vector Regression
Tw-H	Terawatts per Hour
UECM	Unrestricted Error Correction Model
USD	United States Dollar
VAR	Vector Autoregression
VECM	Vector Error Correction Mode

1. INTRODUCTION

Peering into the future of a nation's energy landscape is like navigating the vast, open sea with a map that charts both known and uncharted waters. It's an adventure fraught with uncertainties yet illuminated by a complex blend of science and speculation, facts combined with educated guesses, all aiming to sketch out the energy contours of tomorrow's Bangladesh. At the heart of Bangladesh's journey towards 2050, lies a quest not just of numbers and graphs, but of vision and preparation for the energy demands that the future holds. This journey is crucial as the nation aims to become a high-income country by 2041 and continues its stride beyond, to the year 2050. It will shape everything from urban development to rural livelihoods, from industrial growth to the air we breathe, setting the stage for a sustainable and thriving future.

The Government of Bangladesh (GoB), recognising the criticality of this task, has undertaken the 'Integrated Energy and Power Master Plan (IEPMP)'. This plan aims to sketch out the energy landscape up to 2050, attempting to forecast how much energy the nation will need, where it will come from, and how it can be sustainably sourced and distributed. However, this vision is not just about ensuring lights stay on; it's about crafting policies that touch upon various facets of life, influencing economic growth, environmental sustainability, and social equity.

In embarking on such a forecasting endeavour, we confront a challenge: ensuring that the foundation upon which these forecasts are built is as solid as the intentions behind them. The IEPMP's reliance on potentially optimistic GDP growth rates, constituting intensive economic activities, and straightforward OLS modelling techniques, which might result in potential endogeneity bias and serial correlation issues arose from model misspecification, raises questions about the robustness of its predictions (MoPEMR, 2023; Montgomery, Jennings, & Kulahci, 2008). In other words, the latter issue signifies a model misspecification bias as well. Such concerns are not mere academic quibbles but have real-world implications, affecting everything from how industries plan their future to how communities prepare for changes in their living environment.

Our research revisits energy demand or consumption forecasting in Bangladesh, critically examining the IEPMP and exploring beyond traditional methods like Auto Regressive Integrated Moving Average (ARIMA) and simple OLS regressions, which often overlook the dynamic interplay among variables. Variables in the real-world rarely behave in isolation; their impact and interactions evolve over time, often in unpredictable ways. We employ the Vector Error Correction Model (VECM) for its proficiency in capturing the complex, evolving interactions between factors influencing energy consumption and energy consumption itself. Unlike the IEPMP's reliance on historical data and assumptions, VECM adeptly accommodates the endogenous dynamics of variables, variable unpredictability, and interdependence, offering forecasts that are not only more accurate but also insightful for policy formulation with broader socio-economic considerations.

Our exploration into Bangladesh's energy future reveals that primary energy consumption might be significantly lower than what the IEPMP predicts. By constructing four different scenarios, informed by literature and logical assumptions about future influential factors, we systematically build towards a comprehensive model. Each step of the way, our model consistently forecasts less energy consumption than the IEPMP does.

A challenge identified in our study, and likely overlooked by the IEPMP, was the suitability of incorporating an energy efficiency index into the model. While the IEPMP includes this index, our analysis suggests that its integration could introduce inaccuracies into their forecasts due to the formula used in calculating the index[1] and its problematic fit within the model's specification. The formulation of this index introduces a complexity within the model that could not be adequately resolved without risking inaccuracies.

Following this introduction, Section 2 reviews relevant literature, setting the stage for our study. Section 3 explains the methodology and methods employed, paving the way to Section 4, where we present our findings. Section 5 discusses these findings in the context of their broader implications for policy and planning. Finally, Section 6 concludes our study, summarising key insights and reflecting on the journey of forecasting Bangladesh's energy demand up to 2050.

2. LITERATURE REVIEW

2.1 Model Misspecification of IEPMP

This section is dedicated to examining the diverse array of electricity demand or consumption forecasting methods highlighted in previous studies. Notably, Suganthi and Samuel (2012) have conducted a comprehensive review, identifying 12 distinct forecasting techniques prevalent in the literature. These range from conventional statistical models to more advanced methods. The accuracy of these forecasts has the potential for significant enhancement through the adoption of sophisticated techniques. Innovations such as genetic algorithms, fuzzy logic, Support Vector Regression (SVR), Particle Swarm Optimization (PSO), neural networks, and Accumulated Generating Operation (AGO) have been suggested as ways to refine forecasting accuracy, according to studies cited by Suganthi and Samuel and others in the field (Suganthi & Samuel, 2012). Further exploration by Ghalehkhondabi et al. (2017) grouped forecasting technologies into two main categories: causal methods (including regression models, econometric models, cointegration models, and neural networks) and methods based on historical data (such as annual series, Grey prediction, and autoregressive models) (Ghalehkhondabi, Ardjmand, Weckman, & Young, 2017). Table 1 provides a comprehensive overview of the earlier methodology utilised in order to estimate energy demand forecast or similar literatures, in Bangladesh and globally.

Table 1: Overview of the earlier studies

Authors	Region	Methodology	Variables	Takeaway
Kandananond, (2011)	Thailand	ARDL, ANN and MLR	Population, GDP, stock index, revenue from exporting industrial products and electricity consumption	ANN is more accurate than ARDL and MLR
Kumar & Jain, (2010)	India	Grey-Markov model, GPRM and SSA	Coal, crude-petroleum, natural gas, and electricity consumption by sources	The time series models can be considered as reliable alternative
Azadeh, et. al., (2007)	Iran	Integrated GA and ANN	Electricity consumption, price (value added), number of customers and forecast electricity demand	Integrated GA and ANN performs better than time series model
Kucukali & Baris, (2010)	Turkey	Fuzzy Logic	Electricity consumption and GDP (PPP adjusted)	The model's accuracy is commendable, and its strength is to replicate human thought processes and reasoning

(Table 1 contd.)

[1]Energy Efficiency Index = Total Primary Energy Supply divided by GDP.

(Table 1 contd.)

Authors	Region	Methodology	Variables	Takeaway
Pappas, et al., (2010)	Greece	ARMA	Electricity Demand Load	A new method developed on the multi-model partitioning theory
Kavaklioglu, (2011)	Turkey	SVR	Electricity consumption, population, GNP, imports and exports	The technique is reliable although the econometric test is better
Kwak, Seo, Jang, & Huh, (2013)	South Korea	Input-Output matched, and BCVTB	Energy consumption, weather forecasting, solar radiation calculation	A novel methodology for measuring energy demand
Guo, Chen, Xia, Kang, & Zhang, (2018)	China	SAS-SVECM	Electricity consumption and macroeconomic data	It significantly improves forecasting accuracy and demonstrates strong adaptability.
Shahbaz, Tang, & Shabbir, (2011)	Portugal	UECM and VECM	Energy consumption, economic growth and employment	The model finds causal relationships among the variables
Wadud, et al., (2011)	Bangladesh	OLS	Gas consumption, price, GDP, population	Better econometric models are available
Mondal, Boie, & Denich, (2010)	Bangladesh	LEAP Model	Electricity consumption GDP, electrification rate, population, and urbanisation.	This methodology is considered as bottom-up approach, but endogeneity remains a concern
Debnath, Mourshed, & Chew, (2015)	Bangladesh (Rural)	Constructed their own model, which they claim to be comprehensive	Energy consumption, population, GDP electrification index, public energy conservation index	Heavily relies on assumptions and so, the accuracy of the predictions is highly dependent on the validity and realism of these assumptions
Kabir & Sumi, (2012)	Bangladesh (A power company)	FDM integrated with ANN	Electricity demand, sales price, quality, customer satisfaction level, effect of seasonality & promotions and effect of competitors	Forecasting with neural networks is superior than using time-series frameworks in terms of prediction accuracy
Paul & Uddin, (2011)	Bangladesh	VAR and ARDL	Energy Consumption and Real GDP	VAR provides innovative accounting such as variance decomposition and IRF, while ARDL resonates the similar result

Source: Authors' compilation from various literatures.

Our examination of existing literature reveals that energy consumption forecasts have utilised a range of models, from econometrics and deep learning to machine learning and linear programming. A critical limitation identified is that these models often oversimplify the complexity of real-world energy consumption. This oversight fails to account for the multifaceted nature of energy use, which is influenced not only by economic activities but also by factors such as population size, energy prices, and rapid environmental initiatives, such as reducing CO_2 emissions. Our study aims to address this gap by developing a more nuanced and comprehensive model that realistically integrates the interplay between energy, economic, demographic, and environmental factors. The need for such realistic models is paramount, as they are crucial for accurately forecasting future energy consumption and informing policy decisions that reflect the true dynamics of our world.

2.2 Review of Methodology and Analytical Framework Adopted in IEPMP

Before diving into the specification of VECM, this study wants to point out two major econometric limitations of the model used in the IEPMP. The interim report of IEPMP, provided by JICA, states that the model is estimated through OLS method.

The first that will arise from estimating and forecasting time-series data is that the econometric properties are most likely to be violated. Time series data often exhibit non-stationary behaviour, meaning their statistical properties such as mean, variance, and autocorrelation structure change over time. OLS assumes that the underlying data generating process is stationary.

The standard linear regression model can be written as:

$$Y_t = \beta_0 + \beta_1 X_t + \varepsilon_t$$

For OLS assumptions to hold, among other things, the error terms, ε_t should be independent and identically distributed (i.i.d.) with a mean of zero, constant variance and no autocorrelation. This implies:

$$E(\varepsilon_t) = 0,$$
$$Var(\varepsilon_t) = \sigma^2$$
$$Cov(\varepsilon_t, \varepsilon_{t-1}) = 0; \forall\ t \neq t-1$$

Applying OLS to non-stationary data can lead to spurious regression results, where variables appear to be correlated even when they are not. In time-series analysis, serial autocorrelation is present in most of the times. For example, in an OLS model without autocorrelation, the variance of the estimator, $\hat{\beta}_1$, (for simplicity, we'll focus on the slope coefficient in a simple regression) is given by:

$$Var(\hat{\beta}_1) = \frac{\sigma^2}{\sum_{t=1}^{n}(X_t - \bar{X})^2}$$

and here, $\bar{X}$ is the mean of x_t. However, in the presence of autocorrelation, for example, a first-order autocorrelation where $\varepsilon_t = \rho\varepsilon_{t-1} + \upsilon_t$; ρ is the autocorrelation coefficient and υ_t is a new error term that is i.i.d, the variance of the error term is no longer simply constant. Instead, the error terms are now dependent on their own past values, and this affects the variance of $\hat{\beta}_1$.

Time series data that are non-stationary can sometimes be cointegrated, meaning they share a long-term equilibrium relationship despite being individually non-stationary. OLS fails to account for cointegration among variables, which can lead to biased or incomplete long-term relationship assessments.

Incorporating variables such as energy efficiency and CO_2 intensity, measured by ratios like total energy supply per GDP and total CO_2 emissions per GDP, into a model that already includes GDP as an explanatory variable, introduces several complexities. The use of GDP in both its direct and inverse forms within the same model can lead to multicollinearity and heteroscedasticity, making it challenging to distinguish the impact of one variable from another due to their high correlation. This situation complicates the interpretation of the coefficients and increases the variance of the coefficient estimates, undermining their reliability. Moreover, the model's sensitivity to changes, either in its structure or in the data, is heightened, making it particularly vulnerable to inaccuracies in data measurement.

An additional complication arises from the endogeneity problem. Given the complex relationship between economic growth and energy consumption, simply plotting the data in a straightforward linear model without a careful examination of their dynamic relationship may not be suitable. The intertwined nature of these variables suggests that any change in one is likely to influence or be influenced by changes in the other, violating the assumption of independence required for accurate OLS estimation.

3. DATA AND METHODOLOGY

3.1 Variables

Primary Energy Consumption

Primary energy refers to the raw forms of energy resources, like coal before combustion, uranium, or crude oil, available for extraction and processing. It encompasses both the energy directly consumed by end users for electricity, transportation, and heating, as well as the inefficiencies and losses incurred during the conversion of these raw resources into consumable energy forms. Primary energy consumption is quantified in terawatt-hours (TWh), employing the substitution method[2] for measurement. The data has been sourced from 'Our World in Data' (Ritchie, Rosado, & Roser, 2023a). This variable remains the central point of attention in forecasting efforts. The datapoint spans from 1975 to 2022.

Economic Growth

In our study, economic growth is represented by real GDP, measured in 2015 constant USD. The data has been sources from the World Development Indicators (WDI), the World Bank.[3] The datapoint spans from 1975 to 2022. Energy serves as a pivotal support for production, with the capability to substitute for capital or labour inputs, marking it as a critical driver of economic growth (Ozturk, 2010). For our purpose, in this study, we take the natural logarithm of real GDP for analysis to introduce homoscedasticity, and reduce the skewness of the distribution of GDP values, occurring from the exponential growth of economies over time.

Research has identified diverse patterns of interactions between economic growth and energy consumption: some studies indicate that energy consumption can unilaterally foster economic growth (Lee & Chang, 2005; Karanfil, 2008), while others suggest that economic expansion could unilaterally boost energy usage (Zhang & Cheng, 2009; Ang, 2008). Additionally, evidence of a bidirectional relationship between the two has been found (Polemis & Dagoumas, 2013) whereas some analyses report no significant link (Payne, 2009; Menyah & Wolde-Rufael, 2010). This study

[2]The 'substitution method' is a technique researchers use to adjust for efficiency losses in primary energy consumption, particularly from fossil fuels. This method equates the energy generation from non-fossil sources—like wind and solar—to the equivalent amount of fossil fuel inputs that would be required, assuming these renewable sources are as inefficient as coal or gas. By dividing the energy generated from non-fossil sources by a standard 'thermal efficiency factor,' usually around 0.4, it accounts for the discrepancy in efficiency. Nuclear power, although also subject to thermal losses, is treated similarly. Its output in electricity terms is converted to an equivalent input value through this adjustment, ensuring a consistent basis for comparing energy sources across the board.

[3]URL: https://databank.worldbank.org/source/world-development-indicators

acknowledges a nuanced understanding of the varied relationships between energy consumption and economic growth, which differ significantly based on a country's economic structure and development stage and hence, incorporates this variable in the model.

Total CO_2 Emissions

Total CO_2 emissions are quantified by tracking carbon dioxide (CO_2) released from the combustion of fossil fuels and direct emissions from industrial activities, such as cement and steel production. This encompasses CO_2 emissions from coal, oil, gas, flaring, and various industrial processes. It's important to note that this measurement excludes emissions from land use change, deforestation, soils, or vegetation, focusing solely on fossil fuel and industrial sources. The variable is measured in million tonnes, and it is sourced from 'Our World in Data' (Ritchie, Rosado, & Roser, 2023b). The datapoint spans from 1975 to 2022.

A significant body of research has explored the enduring connections between CO_2 emissions and energy consumption, noting that the reliance on fossil fuels for energy generation significantly contributes to greenhouse gas emissions, with far-reaching implications for climate change and environmental health (Ahmad, Draz, Ozturk, Su, & Rauf, 2020). Including CO_2 emissions in energy forecasting is pivotal for assessing the environmental impact of energy policies and ensuring alignment with global climate commitments. It enables informed decision-making for sustainable energy development, balancing economic growth with environmental preservation and public health objectives. The case of China illustrates this dynamic vividly, where rapid economic expansion and increased energy consumption have substantially heightened greenhouse gas emissions (Riti, Shu, Song, & Kamah, 2017). Furthermore, Chen, Wang, and Zhong, (2019) observed a global rise in carbon dioxide emissions, attributing this trend to the growing demand for energy over recent years. As governments and consumers become increasingly aware of the environmental impact of CO_2 emissions, there is a growing commitment to adopting eco-friendly policies. This heightened consciousness is expected to steer a transition towards more efficient technologies and behaviours that conserve energy, ultimately contributing to a reduction in future energy consumption (Islam, 2023; Calculli, D'Uggento, Labarile, & Ribecco, 2021; Dehdar, Silva, Fuinhas, Koengkan, & Nazeer).

Population Growth Rate

The population growth rate is calculated from the total population of Bangladesh, found in 'Our World in Data' (United Nations, 2022). Including the population growth rate in the model is crucial for accurately forecasting energy consumption, as population dynamics directly influence the demand for energy. A growing population increases the need for residential energy, transportation, and various public services, which in turn affects energy consumption patterns. The relationship between population growth and energy demand is well-documented in the literature, with studies indicating that changes in population size and structure can significantly impact energy use (Kandananond, 2011; Kavaklioglu, 2011). The datapoint spans from 1975 to 2022.

Global Energy Price Index

The Global Energy Price Index is computed based on benchmark prices that reflect the global market, determined by the leading exporter of a specific commodity. These prices are averaged over periods and presented in nominal US dollars. The index is set to a base value of 100 for the year 2016 and is not adjusted for seasonal variations. The data and definition are sourced from Federal Reserve Bank of St. Louis (IMF, 2024). The data is not seasonally adjusted and the observed datapoint spans from 1992 to 2023. The dataset, which is not adjusted for seasonal variations, covers the period from 1992 to 2023. However, given that the timeframe for our other variables extends from 1975 to 2022, we've recalibrated the Global Energy Price Index to reflect the domestic context of Bangladesh by adjusting for the domestic inflation rate[4] using the GDP deflator. This approach is predicated on the understanding that domestic general commodity prices, and consequently domestic energy prices, tend to move in tandem with global energy prices, allowing us to derive a more accurate and contextually relevant pricing index for our analysis (Ergun & Ibrahim, 2013; Gunatilake & Roland-Holst, 2013; Moazzem & Khandker, 2023). The dataset presents a challenge with the anomalously high energy prices in 2022, attributed to the Russia-Ukraine conflict. Given this datapoint's outlier status and the subsequent decline in global energy prices post-2022, along with the diminishing impact of the conflict on energy prices, we opted to exclude this datapoint to prevent skewed results. This allows the VECM to estimate a more representative index value for 2022, as if the Russia-Ukraine war had not influenced the energy market and forecast the scenario accordingly.

3.2 Analytical Framework

Our analytical framework employs Johansen Cointegration and VECM as foundational methodologies to forecast energy consumption. VECM stands out in our analytical framework for its multifaceted strengths, crucial for dissecting the complexities of energy consumption forecasting. Its ability to unveil long-term equilibrium relationships and short-term dynamics among variables like economic growth, CO_2 emissions, and population changes offers a nuanced understanding essential for crafting sustainable energy policies. VECM's methodology, centred on cointegration and error correction, not only ensures variables move in tandem over the long haul but also measures the pace at which deviations from equilibrium are rectified. This precision is invaluable for evaluating the impact of policy shifts or economic disruptions.

Conventional regression estimators, such as Vector Autoregressions (VARs), perform well with covariance-stationary time series but struggle with nonstationary or integrated processes. Granger & Newbold (1974) highlighted this issue through the concept of spurious regressions, demonstrating that significant coefficients could erroneously appear in regressions between two independent random walk processes due to their nonstationary nature. This problem, coupled with Nelson & Plosser's (1982) discovery of the prevalence of unit roots in macroeconomic series, underscored the need for unit root testing and the practice of differencing variables to achieve stationarity before including them in econometric models.

Building on these insights, Engle & Granger (1987) introduced the concept of cointegration, suggesting that even if individual time series are nonstationary, a linear combination of them might exhibit stationarity, indicating a long-term equilibrium relationship. In models with two variables, this concept manifests as the lagged residual from the cointegrating regression -representing the previous disequilibrium - which should theoretically be zero if the long-term relationship holds. For multiple variables, a vector of error-correction terms emerges, corresponding to the number of cointegrating relationships among the series. These developments have significantly influenced econometric modelling.

[4] Data for inflation rate (GDP deflator) can be found in WDI; URL: https://databank.worldbank.org/source/world-development-indicators

Moreover, by addressing endogeneity through its design and aligning closely with economic theory, VECM provides forecasts that are both reliable and theoretically grounded (Johansen, 1995). Such theoretical consistency and methodological robustness make VECM an indispensable tool in energy demand analysis, far surpassing the capabilities of traditional models and deep learning approaches in terms of interpretability and relevance to policymaking.

To enrich our analysis, we have developed four scenarios through structural progression, each adding layers of complexity and realism to our energy consumption forecast:

(i) Scenario 1 (Energy Consumption and GDP)

This initial scenario aligns with previous literature by correlating energy consumption with economic activities, reflected by GDP. The aim here is to establish a baseline that allows for comparison with studies that focus solely on the economic growth of energy demand. This scenario serves as a foundation, highlighting the importance of extending beyond economic factors to capture a fuller picture of energy consumption dynamics.

(ii) Scenario 2 (Energy Consumption, GDP, and CO_2 Emissions)

The second scenario incorporates CO_2 emissions together with energy consumption and economic activities, acknowledging the increasing focus on environmental sustainability by both governments and consumers. This scenario underlines the dual goals of CO_2 emission reduction for environmental preservation and the alignment with policy incentives to counter climate change effects, necessitating an adjustment in energy consumption forecasts to reflect shifts towards sustainability. Furthermore, this scenario will provide a basis for contrasting the energy consumption landscape when considering only economic growth against a more comprehensive view that includes environmental factors.

(iii) Scenario 3 (Energy Consumption, GDP, CO_2 Emissions and Population Growth Rate)

The third scenario further expands the model to include population growth rate. In Bangladesh, a changing demographic landscape, characterised by a declining population growth rate, presents a crucial factor in predicting future energy demand. The inclusion of demographic factors, such as population growth, in analysing energy consumption recognises that economic activities alone do not dictate energy demand. As the population increases, there's a direct rise in residential energy needs for heating, cooling, lighting, and appliance use. Additionally, population growth drives urbanisation, which further escalates demand for commercial energy in services and industries, and for transportation.

(iv) Scenario 4 (Energy Consumption, GDP, CO_2 Emissions, Population Growth Rate and Global Energy Price Index)

The inclusion of pricing aspect completes our analytical framework. and it acknowledges the pivotal role of price in shaping demand and consumption. Drawing from both New-Classical and New-Keynesian economic theories, this scenario examines how energy prices influence consumption patterns in the short and long run. Despite New-Keynesian suggestions of price stickiness in the short-term, the overarching consensus is that price mechanisms play a critical role in determining demand. By integrating the Global Energy Price Index, our framework aims to provide a comprehensive overview that encapsulates the multifaceted nature of energy consumption determinants.

Finally, this study aims to project each developed scenario up to the year 2050 while considering 2030 and 2041 as important milestones, utilising the VECM for its forecasting strengths. VECM is notably proficient in short-term forecasting, capitalising on the data provided by the error correction mechanism to refine predictions by accounting for deviations from the long-term equilibrium. This feature is crucial for accurate short-term forecasts, as it allows for immediate adjustments based on the system's dynamics. For long-term forecasts, the cointegration relationships encoded within the VECM ensure that the forecasts adhere to the underlying equilibrium dynamics, offering a credible extension of current trends into the future and hence, positions itself as an ideal tool for forecasting energy consumption scenarios over extended periods.

3.3 Methodological Steps

Initially, trend analysis via Ordinary Least Squares (OLS) regression pinpointed variables with trends, followed by detrending to mitigate these effects. It can be observed that trend is present among all the variables (see Appendix B). However, detrending does not make the variables stationary and so, presence of unit root can be suspected. To ascertain stationarity and identify any unit roots present, Augmented Dickey-Fuller (ADF) and Phillip-Peron unit root tests were employed, leading to the differencing of variables as necessary to achieve stationarity. The summary of the integration of order for each variable is summarized in the following table (see Appendix A for detailed calculation):

Table 2: Summary table of integration of order for each variable

Variables	Integration of Order	Lags
e	I(1)	0
lngdp	I(1)	0
co2	I(1)	0
popgr	I(1)	0
p_hat	I(1)	0

Source: Author's calculation.

Achieving stationarity necessitates taking the first difference of each variable. Thus, detrending each variable that shows a linear trend becomes redundant since differencing effectively removes the deterministic trend, leading to stationarity. However, the presence of a non-linear trend in the Global Energy Price Index (p) raises concerns, as mere first differencing does not confirm stationarity for this variable. In such cases, it becomes crucial to detrend p (represented by p_ hat) and further examine if its detrended form achieves stationarity. Opting against taking the second difference of this variable is strategic; doing so would preclude the use of VECM and might introduce unnecessary noise or standard error into the model.

Since all the variables are integrated of order one, we can perform Johansen cointegration to check for long run relationships for each scenario. Since Johansen cointegration is present in all scenarios (see Appendix D), we employ VECM in our analysis. Otherwise, we might need to utilise unrestricted VAR. Before performing VECM, it is important to find the optimal lag of VAR and rank of Johansen cointegration. The optimal lag of VAR can be found by utilising selection order criteria (AIC, SBIC, HQC). The summary table of optimal lag and rank test can be illustrated below:

Table 3: Summary table of optimal lag and rank order of cointegration for each scenario

Scenarios	Optimal lags	Rank order of cointegration
Scenario 1	2	1
Scenario 2	4	1
Scenario 3	2	1
Scenario 4	2	2

Source: Authors' calculation.

In Scenario 1, selecting optimal lags =1 resulted in an unstable VECM, as determined by examining its eigenvalues to assess stability. Given the goal of forecasting values with an emphasis on long-term relationships, ensuring model stability is paramount. Therefore, to achieve a stable VECM, we opted for setting the VAR lags to 5 (see Table G.1 and Table G.2 from Appendix G).

As a concluding step, the model was employed to predict future values of the endogenous variables. For variable represented in logarithmic form, such as GDP, the anti-log was taken to revert these values back to their original scale, facilitating a direct comparison with the forecasts provided by the IEPMP.

Stata MP 16.0 and Microsoft Excel 2021 were used for data analysis.

3.4 Model Specification

VECM, an extension of VAR, is designed to solve and address these issues by effectively capturing the long-term equilibrium relationships between integrated variables while also accounting for short-term dynamics. This approach allows for the inclusion of both levels and differences of the data, thus handling non-stationarity without discarding valuable long-run information. This methodology not only mitigates the concerns of partial multicollinearity and heteroscedasticity but also directly addresses endogeneity by incorporating the dynamics of variables influencing each other over time (Montgomery, Jennings, & Kulahci, 2008).

The model specification for the four scenarios can be illustrated in the following manner:

Scenario 1

Johansen Cointegration Test:

First, we start with a VAR model for the integrated variables $X_t' = (e_t, lngdp_t)'$ in levels due to the fact that both variables are I(1):

$$\Delta X_t' = \mu + \Phi D_t + \Gamma_1 \Delta X_{t-1}' + \cdots + \Gamma_{p-1} \Delta X_{t-p+1}' + \Pi X_{t-p}' + \epsilon_t$$

Where:

μ is a vector of intercepts, D_t represents deterministic terms (such as trends or seasonal dummies) with coefficients matrix Φ, Γ_i are the matrices of short-run coefficients, Π is the long-run relationship matrix, and ϵ_t is the vector of error terms.

Selection of Rank for Cointegration:

The matrix *Π* can be decomposed into *α*β′, where α contains the loading factors and β contains the cointegration vectors. The rank of the *Π* matrix *(r)*, which is the number of cointegration relationships, is determined through Johansen's Trace and Maximum Eigenvalue test. In this study, we have utilized the Trace statistics and Trace test checks the null hypothesis H_0:r = r_0 against the alternative H_0:r = r_0 for r_0 = 0, 1,......., n - 1, where n is the number of variables in X_t.

VECM Specification:

Assuming that r cointegrating relationships are identified, the VECM model is specified as:

$$\Delta X_t = \mu + \Phi D_t + \sum_{i=1}^{p-1} \Gamma_i \Delta X_{t-1} + \alpha\beta' X_{t-1} + \epsilon_t$$

the term $\alpha\beta' X_{t-1}$ introduces the error correction mechanism, where $\beta' X_{t-1}$ represents the deviation from the long-term equilibrium in the previous period, and α contains the speed of adjustment parameters indicating how quickly variables return to equilibrium.

For the specific case of energy consumption (e) and logarithm of GDP (lngdp) if we find one cointegrating relationship (r = 1), the VECM simplifies to:

$$(1)\ \Delta e_t = \mu_e + \sum_{i=1}^{p-1} \Gamma_{e,i} \Delta e_{t-i} + \sum_{i=1}^{p-1} \Gamma_{lngdp,i} \Delta lngdp_{t-i} + \alpha_e(\beta_e e_{t-1} + \beta_{lngdp} lngdp_{t-1}) + \epsilon_{e,t}$$

$$(2)\ \Delta lngdp_t = \mu_{lngdp} + \sum_{i=1}^{p-1} \Gamma_{e,i} \Delta e_{t-i} + \sum_{i=1}^{p-1} \Gamma_{lngdp,i} \Delta lngdp_{t-i} + \alpha_{lngdp}(\beta_e e_{t-1} + \beta_{lngdp} lngdp_{t-1}) + \epsilon_{lngdp,t}$$

The specification for Johansen Cointegration and the criteria for selecting the rank will remain consistent across all scenarios, identical to that established in Scenario 1. The only variation will involve the vector of endogenous variables, which will be adjusted to reflect the specific composition of each scenario.

Scenario 2

Under this scenario, the vector of endogenous variables is updated to X_t^2 =(e_t, $lngdp_t$,co2)′ and the VECM specification, when cointegration rank, r = 1, can be written as:

$$(3)\ \Delta e_t = \mu_e + \sum_{i=1}^{p-1} \Gamma_{e,i}\Delta e_{t-i} + \sum_{i=1}^{p-1} \Gamma_{lngdp,i}\Delta lngdp_{t-i} + \sum_{i=1}^{p-1} \Gamma_{co2,i}\Delta co2_{t-i} + \alpha_e(\beta_e e_{t-1} + \beta_{lngdp} lngdp_{t-1} + \beta_{co2} co2_{t-1}) + \epsilon_{e,t}$$

$$(4)\ \Delta lngdp_t = \mu_{lngdp} + \sum_{i=1}^{p-1} \Gamma_{e,i}\Delta e_{t-i} + \sum_{i=1}^{p-1} \Gamma_{lngdp,i}\Delta lngdp_{t-i} + \sum_{i=1}^{p-1} \Gamma_{co2,i}\Delta co2_{t-i} + \alpha_{lngdp}(\beta_e e_{t-1} + \beta_{lngdp} lngdp_{t-1} + \beta_{co2} co2_{t-1}) + \epsilon_{lngdp,t}$$

$$(5)\ \Delta co2_t = \mu_{co2} + \sum_{i=1}^{p-1} \Gamma_{e,i}\Delta e_{t-i} + \sum_{i=1}^{p-1} \Gamma_{lngdp,i}\Delta lngdp_{t-i} + \sum_{i=1}^{p-1} \Gamma_{co2,i}\Delta co2_{t-i} + \alpha_{co2}(\beta_e e_{t-1} + \beta_{lngdp} lngdp_{t-1} + \beta_{co2} co2_{t-1}) + \epsilon_{lngdp,t}$$

Scenario 3

Under the 3rd scenario, in the similar fashion, the vector of endogenous variables is updated to X_t^3=(e_t, lngdp$_t$,co2,popgr)' and the VECM specification, when cointegration rank, r = 1, can be written as:

$$(6)\ \Delta e_t = \mu_e + \sum_{i=1}^{p-1} \Gamma_{e,i}\Delta e_{t-i} + \sum_{i=1}^{p-1} \Gamma_{lngdp,i}\Delta lngdp_{t-i} + \sum_{i=1}^{p-1} \Gamma_{co2,i}\Delta co2_{t-i} + \sum_{i=1}^{p-1} \Gamma_{popgr,i}\Delta popgr_{t-i} + \alpha_e(\beta_e e_{t-1} + \beta_{lngdp} lngdp_{t-1} + \beta_{co2} co2_{t-1} + \beta_{popgr} popgr_{t-1}) + \epsilon_{e,t}$$

$$(7)\ \Delta lngdp_t = \mu_{lngdp} + \sum_{i=1}^{p-1} \Gamma_{e,i}\Delta e_{t-i} + \sum_{i=1}^{p-1} \Gamma_{lngdp,i}\Delta lngdp_{t-i} + \sum_{i=1}^{p-1} \Gamma_{co2,i}\Delta co2_{t-i} + \sum_{i=1}^{p-1} \Gamma_{popgr,i}\Delta popgr_{t-i} + \alpha_{lngdp}(\beta_e e_{t-1} + \beta_{lngdp} lngdp_{t-1} + \beta_{co2} co2_{t-1} + \beta_{popgr} popgr_{t-1}) + \epsilon_{lngdp,t}$$

$$(8)\ \Delta co2_t = \mu_{co2} + \sum_{i=1}^{p-1} \Gamma_{e,i}\Delta e_{t-i} + \sum_{i=1}^{p-1} \Gamma_{lngdp,i}\Delta lngdp_{t-i} + \sum_{i=1}^{p-1} \Gamma_{co2,i}\Delta co2_{t-i} + \sum_{i=1}^{p-1} \Gamma_{popgr,i}\Delta popgr_{t-i} + \alpha_{co2}(\beta_e e_{t-1} + \beta_{lngdp} lngdp_{t-1} + \beta_{co2} co2_{t-1} + \beta_{popgr} popgr_{t-1}) + \epsilon_{co2,t}$$

$$(9)\ \Delta popgr_t = \mu_{popgr} + \sum_{i=1}^{p-1} \Gamma_{e,i}\Delta e_{t-i} + \sum_{i=1}^{p-1} \Gamma_{lngdp,i}\Delta lngdp_{t-i} + \sum_{i=1}^{p-1} \Gamma_{co2,i}\Delta co2_{t-i} + \sum_{i=1}^{p-1} \Gamma_{popgr,i}\Delta popgr_{t-i} + \alpha_{popgr}(\beta_e e_{t-1} + \beta_{lngdp} lngdp_{t-1} + \beta_{co2} co2_{t-1} + \beta_{popgr} popgr_{t-1}) + \epsilon_{popgr,t}$$

Scenario 4

Under the final scenario, in the previous manner, the vector of endogenous variables can be updated to X_t^4=(e_t, lngdp$_t$,co2,popgr,p_hat)'. However, the Johansen cointegration rank, r = 2 in this case. The model can be illustrated in this case as:

$$(10)\ \Delta e_t = \mu_e + \sum_{i=1}^{p-1} \Gamma_{e,i}\Delta e_{t-i} + \sum_{i=1}^{p-1} \Gamma_{lngdp,i}\Delta lngdp_{t-i} + \sum_{i=1}^{p-1} \Gamma_{co2,i}\Delta co2_{t-i} + \sum_{i=1}^{p-1} \Gamma_{popgr,i}\Delta popgr_{t-i} + \sum_{i=1}^{p-1} \Gamma_{p\_hat,i}\Delta p\_hat_{t-i} + \sum_{j=1}^{2} \alpha_e B_j{}' X_{t-1} + \epsilon_{e,t}$$

$$(11)\ \Delta lngdp_t = \mu_{lngdp} + \sum_{i=1}^{p-1} \Gamma_{e,i}\Delta e_{t-i} + \sum_{i=1}^{p-1} \Gamma_{lngdp,i}\Delta lngdp_{t-i} + \sum_{i=1}^{p-1} \Gamma_{co2,i}\Delta co2_{t-i} + \sum_{i=1}^{p-1} \Gamma_{popgr,i}\Delta popgr_{t-i} + \sum_{i=1}^{p-1} \Gamma_{p\_hat,i}\Delta p\_hat_{t-i} + \sum_{j=1}^{2} \alpha_{lngdp} B_j{}' X_{t-1} + \epsilon_{lngdp,t}$$

$$(12)\ \Delta co2_t = \mu_{co2} + \sum_{i=1}^{p-1} \Gamma_{e,i}\Delta e_{t-i} + \sum_{i=1}^{p-1} \Gamma_{lngdp,i}\Delta lngdp_{t-i} + \sum_{i=1}^{p-1} \Gamma_{co2,i}\Delta co2_{t-i} + \sum_{i=1}^{p-1} \Gamma_{popgr,i}\Delta popgr_{t-i} + \sum_{i=1}^{p-1} \Gamma_{p\_hat,i}\Delta p\_hat_{t-i} + \sum_{j=1}^{2} \alpha_{co2} B_j{}' X_{t-1} + \epsilon_{co2,t}$$

$$(13)\ \Delta popgr_t = \mu_{popgr} + \sum_{i=1}^{p-1} \Gamma_{e,i}\Delta e_{t-i} + \sum_{i=1}^{p-1} \Gamma_{lngdp,i}\Delta lngdp_{t-i} + \sum_{i=1}^{p-1} \Gamma_{co2,i}\Delta co2_{t-i} + \sum_{i=1}^{p-1} \Gamma_{popgr,i}\Delta popgr_{t-i} + \sum_{i=1}^{p-1} \Gamma_{p\_hat,i}\Delta p\_hat_{t-i} + \sum_{j=1}^{2} \alpha_{popgr} B_j{}' X_{t-1} + \epsilon_{popgr,t}$$

$$(14)\ \Delta p\_hat_t = \mu_{p\_hat} + \sum_{i=1}^{p-1} \Gamma_{e,i} \Delta e_{t-i} + \sum_{i=1}^{p-1} \Gamma_{lngdp,i} \Delta lngdp_{t-i} + \sum_{i=1}^{p-1} \Gamma_{co2,i} \Delta co2_{t-i} + \sum_{i=1}^{p-1} \Gamma_{popgr,i} \Delta popgr_{t-i} + \sum_{i=1}^{p-1} \Gamma_{p\_hat,i} \Delta p\_hat_{t-i} + \sum_{j=1}^{2} \alpha_{p\_hat,j} B_j' X_{t-1} + \epsilon_{p\_hat,t}$$

4. FINDINGS

4.1 Findings from Scenario-1 (Energy Consumption and GDP)

Short-run Dynamics: The error correction term for energy consumption (L._ce1) with a coefficient of -0.100, as seen in Table E.1 (Appendix E), signifies that any short-term deviation from the long-term equilibrium path is corrected by approximately 10 per cent each year. For GDP, the absence of a significant error correction term indicates its short-run dynamics are not strongly tied to the equilibrium relationship with energy consumption.

In the energy consumption equation, the lag 4 difference (L4D.e), with a coefficient of 0.746 (Table E.1 from Appendix E), highlights a notable rebound effect, suggesting that past fluctuations in energy consumption significantly impact its current level. For the logarithm of GDP (lngdp), the lag 4 difference (L4D.lngdp) shows a negative coefficient of -0.281 (Table E.1 from Appendix E), indicating that past GDP values influence its present trend in a complex manner, likely reflecting delayed economic responses to external shocks.

Long-term Relationship: The long-term inverse relationship between GDP and energy consumption constitutes a significant case where a 1 per cent increase in GDP is associated with a decrease in energy consumption, adjusted for the scale of the variables involved. This phenomenon can also be explained by the prospect of Bangladesh achieving energy efficiency in the future. The constant term in the cointegration equation suggests a baseline level of energy consumption that exists independently of GDP fluctuations, providing a reference point for the equilibrium state of energy consumption (see table F.1 from Appendix F).

Stability and Forecast of Scenario 1: The model is found stable under eigenvalues condition (see Table G.2 from Appendix G). For our purpose of forecasting energy consumption, we would like to highlight the energy consumption of 2030, 2041 and 2050[5], compared to that of 2019, which was taken as the reference year of IEPMP (MoPEMR, 2023). The summary of the energy forecast from Table H.1 (Appendix H) is given below:

[5] The selection of these years is strategic, aligning with the government's commitment to achieve various energy-related targets by 2030, 2041, and 2050. These benchmarks are set forth in an array of the government's policies, plans, and a comprehensive master plan, guiding the nation's energy strategy.

Table 4: Summary of Energy Consumption Forecast under Scenario-1

Year	Primary Energy Consumption (Tw-H)	Change (Times Changed)	IEPMP Forecast[6] (Times Changed)
2019	483	-	-
2030	597	1.24 times	1.68 times
2041	727	1.51 times	2.6 times
2050	823	1.7 times	3.75 times

Source: Authors' calculation and IEPMP (MoPEMR, 2023).

4.2 Findings from Scenario-2 (Energy Consumption, GDP, and CO_2 Emissions)

Short-run Dynamics: The coefficients for the error correction term are significant across all three equations. The positive and significant coefficient in the energy consumption equation suggests a notable and swift adjustment towards equilibrium. The lagged differences show varying levels of impact across the three variables. Notably, L3D.e shows a significant negative impact on CO_2 emissions, indicating that past values of energy consumption influence current CO_2 emission levels. It shows a capacity for immediate adjustments following deviations from equilibrium, suggesting a responsive system to external shocks and policy changes. For D_lngdp, the third lag (L3D.lngdp) is positively significant, suggesting that past GDP levels can have a delayed effect on current GDP growth. The constant term in the D_lngdp equation is significant, indicating a consistent growth in GDP, independent of the model's other variables (see Table E.2 from Appendix E).

Long-term Relationship: Table F.2 (Appendix F) shows a long-term relationship among energy consumption, logarithm of GDP, and CO_2 emissions. Specifically, the coefficient for lngdp is 14.23, though not statistically significant, suggesting a tentative long-term positive relationship with energy consumption. The coefficient for CO_2 emissions (−4.26) is highly significant, underscoring a robust negative relationship with energy consumption in the long-term (see Table F.2 from Appendix F).
Stability and Forecast of Scenario 2: The model is found stable under eigenvalues condition (see Table G.3 from Appendix G). The summary of the energy forecast from Table H.2 (Appendix H) is given below:

Table 5: Summary of Energy Consumption Forecast under Scenario-2

Year	**Primary Energy Consumption (Tw-H)**	**Change (Times Changed)**	**IEPMP Forecast (Times Changed)**
2019	483	-	-
2030	660	1.37 times	1.68 times
2041	910	1.88 times	2.6 times
2050	1115	2.31 times	3.75 times

Source: Authors' calculation and IEPMP (MoPEMR, 2023).

[6]One methodological limitation identified in the IEPMP concerns the calculation of Final Energy Consumption. The formula used in IEPMP for Final Energy Consumption: *Energy Deman = f* [*income*(+), *energy price*(-), *previous demand*(+)]. The formulation problem is that, econometrically, these linear models fail to capture external shocks and the inter-dynamics among variables, both in the long and short-term. Moreover, endogeneity bias presents a significant concern for such linear estimations. An essential aspect of time-series analysis is determining whether variables are stationary. These econometric assumptions are absent in the IEPMP's final energy consumption demand model formulation. Since the role of systematic loss from primary to final energy consumption remains unchanged in the IEPMP's forecasts as well, comparing year-to-year changes by calculating primary energy consumption offers similar, yet improved significance, as modelling the latter in our manner addresses the aforementioned issues. Therefore, this study compares changes in energy consumption between the IEPMP forecasts and our own.

4.3 Findings from Scenario-3 (Energy Consumption, GDP, CO_2 Emissions and Population Growth Rate)

Short-run Dynamics: From Table E.3, it can be observed that for all variables, the coefficients are significant, indicating that deviations from the long-term equilibrium are being corrected. Energy consumption adjusts at a rate of 27 per cent per period, suggesting a moderate speed of adjustment towards equilibrium. The coefficients for the logarithm of GDP, CO_2 emissions, and population growth rate are also significant, highlighting their respective adjustments to long-term equilibrium. The lagged differences of the variables exhibit mixed impacts on each other. Notably, LD.lngdp negatively impacts itself, suggesting some resistance to growth in the short-term. LD.co2 shows a significant negative impact on CO_2 emissions, indicating a self-correcting mechanism. Population growth rate (LD.popgr) significantly impacts itself positively, emphasising its momentum and suggesting that previous rates of population growth spur further growth.

Long-term Relationship: From Table F.3 (Appendix F), it is visible that the coefficients for the long-term relationships show that the logarithm of GDP and population growth rate both have significant negative relationships with primary energy consumption. Specifically, a unit increase in the logarithm of GDP and population growth rate is associated with decreases in energy consumption by 58.714 and 54.122 units, respectively. CO_2 emissions also have a significant negative relationship with energy consumption, highlighting environmental impacts.

Stability and Forecast of Scenario-3: The model is found stable under eigenvalues condition (see Table G.4 from Appendix G). The summary of the energy forecast from Table H.3 (Appendix H) is given below:

Table 6: Summary of Energy Consumption Forecast under Scenario-3

Year	Primary Energy Consumption (Tw-H)	Change (Times Changed)	IEPMP Forecast (Times Changed)
2019	483	-	-
2030	631	1.31 times	1.68 times
2041	767	1.6 times	2.6 times
2050	893	1.85 times	3.75 times

Source: Authors' calculation and IEPMP (MoPEMR, 2023).

4.4 Findings from Scenario-4 (Energy Consumption, GDP, CO_2 Emissions, Population Growth Rate and Global Energy Price Index)

Short-run Dynamics: From Table E.4 (Appendix E), it can be noted that the L._ce1 coefficients across different variables in Scenario 4 reveal a complex interplay of adjustments towards long-term equilibrium following shocks or deviations. These adjustments are variable-specific, with energy consumption, GDP, and CO_2 emissions showing tendencies to increase as part of their adjustment processes, whereas population growth rate exhibits a reduction. For the logarithm of GDP (D.lngdp), the presence of a significantly negative coefficient within the VECM underscores a distinct adjustment mechanism for GDP in response to deviations from its long-term equilibrium. This negative coefficient suggests that, following a shock, GDP tends to decrease as part of its adjustment process back towards equilibrium. Essentially, this indicates that economic output has a unique correction path, which operates somewhat autonomously, reflecting its sensitivity to imbalances and its inherent tendency to restore stability through contraction.

A negative but not statistically significant coefficient for energy consumption (LD.e) implies that past levels of energy consumption have a dampening effect on its current level, though this effect isn't strong enough to be deemed significant. This could suggest some form of inertia or resistance to rapid changes in energy consumption patterns. The negative and significant impact on the logarithm of GDP signals that previous GDP values negatively influence its present trend. This could reflect economic adjustments or reactions to past economic activities. The dynamics affecting CO_2 emissions and population growth are highlighted by their respective lagged terms. For CO_2 emissions, the negative coefficient on LD.co2 (-0.833, significant at the 1 per cent level) suggests a self-correcting trend in emissions. Conversely, a significant positive coefficient for population growth rate (LD.popgr), (0.588, significant at the 1 per cent level) emphasises that past growth rates positively influence current population growth, suggesting a momentum effect.

Long-term Relationship: Table F.4 (Appendix F) reveals two distinct cointegrating vectors (_*ce1 and _ce2*), indicating long-term equilibrium relationships among these variables. For the first cointegrating vector (_*ce1*), the coefficients suggest a significant negative relationship between **CO_2** emissions and energy consumption, highlighting a strong inverse association that aligns with expectations of environmental impact on energy use. The significant negative relationship between CO_2 emissions and energy consumption in the first vector suggests an environmental constraint on energy usage, potentially reflecting efficiency improvements or shifts towards less carbon-intensive energy sources. Interestingly, the global energy price index (*p_hat*) shows a positive relationship, suggesting that higher global energy prices are associated with an increase in primary energy consumption in the long run. The positive relationship between energy prices and consumption highlights the role of market dynamics in energy demand, suggesting that higher prices do not necessarily deter consumption, possibly due to the inelastic nature of energy demand or increases in energy efficiency. The population growth rate (*popgr*) in this vector, however, does not show a significant long-term impact on energy consumption.

The second cointegrating vector (_*ce2*) underscores a unique set of relationships, with the logarithm of GDP (*lngdp*) being omitted due to collinearity and thus set as the reference variable. Here, CO_2 emissions and population growth rate show significant coefficients. Notably, the global energy price index (*p_hat*) has a minimal and non-significant impact in this vector, contrasting with its role in the first vector.

Stability and Forecast of Scenario-4: The model is found stable under eigenvalues condition (see Table G.5 from Appendix G). The summary of the energy forecast from Table H.4 (Appendix H) is given below:

Table 7: Summary of Energy Consumption Forecast under Scenario-4

Year	Primary Energy Consumption (Tw-H)	Change (Times Changed)	IEPMP Forecast (Times Changed)
2019	483	-	-
2030	655	1.36 times	1.68 times
2041	849	1.76 times	2.6 times
2050	996	2.06 times	3.75 times

Source: Authors' calculation and IEPMP (MoPEMR, 2023).

A summary of our findings can be illustrated below:

(a) A consistent theme in all scenarios is the significant role of the error correction term, especially for energy consumption, which indicates a mechanism for returning to long-term equilibrium after short-term shocks. This reflects the resilience of the energy sector to external pressures and its tendency to stabilise around a long-term path. Furthermore, the long-term relationships identified in each scenario underscore the inverse relationship between energy consumption and CO_2 emissions, highlighting the impact of environmental considerations on energy usage.

(b) The introduction of additional variables in each subsequent scenario reveals varying degrees of impact on short-term dynamics and long-term relationships. Notably, the inclusion of the global energy price index in Scenario 4 introduces a new dimension to the analysis, illustrating the sensitivity of energy consumption to price fluctuations. Differences in the coefficients and significance levels across scenarios emphasise the complex interplay between economic growth, environmental factors, and market dynamics.

(c) The synthesis of findings from all scenarios underscores the multifaceted nature of energy consumption dynamics. While economic growth (represented by the logarithm of GDP) generally encourages energy consumption, this relationship is moderated by environmental concerns (CO_2 emissions) and demographic changes (population growth rate). The global energy price index further complicates this relationship, suggesting that energy prices can both stimulate and restrain consumption, depending on the broader economic and environmental context.

(d) A noteworthy observation is that the forecasts of energy consumption in all scenarios are consistently lower than those projected by the IEPMP.

- Scenario 1 Forecast: Between 2019 and 2050, our study predicts an increase in primary energy consumption from 41.25 million tonnes of oil equivalent (mtoe), equivalent to 483 terawatt-hours (Tw-H), to 70.77 mtoe (823 Tw-H), marking a 1.7-fold growth. This projection starkly contrasts with the Integrated Energy and Power Master Plan's (IEPMP) anticipation of final energy consumption reaching up to 155 mtoe under the Advanced Technology Scenario (ATS) and 177 mtoe under the Business as Usual (BAU) scenario, which equates to 3.75 times increase. Notably, primary energy consumption generally surpasses final energy consumption due to the exclusion of system and distribution losses in the latter. However, our primary energy consumption forecast remains substantially lower than the final energy consumption figures posited by the IEPMP, implying the overly inflated forecast of the IEPMP.
- Scenario 2 Forecast: From 2019 to 2050, primary energy consumption is projected to climb from 41.25 mtoe (483 Tw-H) to 95.873 mtoe (1115 Tw-H), achieving a 2.31-fold increase. This forecast is positioned against the IEPMP's expected final energy consumption of 155 mtoe in the ATS and 177 mtoe in the BAU scenario, showcasing a growth of 3.75 times according to IEPMP predictions.
- Scenario 3 Forecast: Our findings suggest a rise in primary energy consumption from 41.25 mtoe (483 Tw-H) in 2019 to 76.78 mtoe (893 Tw-H) by 2050, reflecting 1.85 times increase. This outcome is juxtaposed with the IEPMP's final energy consumption forecast of 155 mtoe under ATS and 177 mtoe under BAU, which anticipates a 3.75-fold growth, highlighting the conservative nature of our estimates in comparison.
- Scenario 4 Forecast: Over the period from 2019 to 2050, we expect primary energy consumption to augment from 41.25 mtoe (483 Tw-H) to 85.64 mtoe (996 Tw-H), indicating a 2.06 times

upsurge. This is measured against the IEPMP's projection of 3.75 times increase in final energy consumption, from 155 mtoe in the ATS to 177 mtoe in the BAU scenario, further evidencing the prudence of our model's forecasts.

This discrepancy could stem from the model's capacity to integrate and adjust for external shocks, endogeneity, and inter-variable dynamics, which might not be fully accounted for in IEPMP's linear estimation approach. The VECM's incorporation of short-run dynamics and long-term equilibriums, combined with the systematic adjustment for deviations from equilibrium, provides a more responsive and potentially realistic outlook on future energy consumption patterns.

5. POLICY RECOMMENDATIONS

In light of the findings from our comprehensive analysis across four scenarios, we propose targeted policy recommendations to optimize Bangladesh's energy strategy and align it more closely with realistic consumption forecasts and sustainable development goals.

i) Refinement of Energy Consumption Forecasting Methods:

Our analysis indicates a significant discrepancy between the Integrated Energy and Power Master Plan (IEPMP)'s projections and our more nuanced VECM-based forecasts. This disparity underscores the need for a methodological overhaul in how aggregate energy consumption forecasts are derived. Specifically, the IEPMP should consider adopting advanced econometric models like VECM that account for the dynamic interplay between economic growth, environmental factors, and energy consumption. Such models offer a more accurate reflection of long-term equilibrium and short-term adjustments, providing a solid foundation for energy planning. Additionally, future studies should aim to disaggregate energy consumption forecasts by sector, employing VECM, unlike the IEPMP. This approach would offer deeper insights into sector-specific energy demands, enabling more targeted and efficient energy policies and strategies.

iii) Revision of Energy-Related Plans and Policies:

The implications of aiming for inflated energy consumption targets are manifold, including undue fiscal strain, potential budget deficits, and increased reliance on foreign loans. It's paramount that energy plans and policies are re-evaluated in light of our findings to prevent these economic vulnerabilities. Policies should be designed to support sustainable energy growth, factoring in the realistic energy consumption forecasts provided by our analysis. By tailoring policies to more realistic forecasts, Bangladesh can ensure that its energy strategy is both economically viable and environmentally sustainable, reducing the risk of fiscal imbalances and enhancing the country's resilience to external economic shocks.

In summary, the shift towards a more data-driven and realistic approach in forecasting and planning for energy consumption is not merely a recommendation but a necessity. By adopting sophisticated forecasting models, setting achievable renewable energy targets, and revising energy policies accordingly, Bangladesh can chart a path toward sustainable energy utilisation that supports economic growth while safeguarding environmental and fiscal health.

6. CONCLUSION

As we draw the curtains on this study, it's clear that forecasting energy consumption is not just about numbers and models; it's about envisioning a future where economic growth, environmental stewardship, and energy sustainability dance in harmony. Through the lens of our analysis, Bangladesh's energy narrative unfolds, revealing paths less trodden but more aligned with the realities of our dynamic world.

Our journey through progressive development of various scenarios has not only challenged the status quo of energy forecasting but also laid the groundwork for a future where goals are not just ambitious but achievable. This study is a call to action for policymakers, urging a recalibration of strategies and a deeper understanding of the forces that shape our energy landscape.

The journey does not end here; it marks the beginning of a recalibrated course towards energy sustainability. This study's insights beckon policymakers, researchers, and industry stakeholders to rally under the banner of informed decision-making, grounded in the robustness of advanced econometric modelling. As Bangladesh strides forward, the nation's energy strategy, fortified by the pillars of realism and sustainability, promises a horizon where economic growth and environmental preservation converge.

Let this study be a beacon, illuminating the path to an energy-efficient future, where ambitious goals are anchored in the bedrock of empirical evidence and strategic foresight. In the pursuit of a balanced energy ecosystem, our findings chart a course towards not just meeting the energy needs of today, but nurturing the well-being of generations to come. The quest for a sustainable energy future is a shared voyage—let us navigate these waters with wisdom, courage, and the insights gleaned from our exploration.

REFERENCES

Ahmad, F., Draz, M. U., Ozturk, I., Su, L., & Rauf, A. (2020). Looking for asymmetries and nonlinearities: The nexus between renewable energy and environmental degradation in the Northwestern provinces of China. *Journal of Cleaner Production, 266*, 121714. https://doi.org/10.1016/j.jclepro.2020.121714

Ang, J. B. (2008). Economic development, pollutant emissions and energy consumption in Malaysia. *Journal of Policy Modeling, 30*(2), 271-278. https://doi.org/10.1016/j.jpolmod.2007.04.010

Azadeh, A., Ghaderi, S. F., Tarverdian, S., & Saberi, M. (2007). Integration of artificial neural networks and genetic algorithm to predict electrical energy consumption. *Applied Mathematics and Computation, 186*(2), 1731-1741. https://doi.org/10.1016/j.amc.2006.08.093

Calculli, C., D'Uggento, A. M., Labarile, A., & Ribecco, N. (2021). Evaluating people's awareness about climate changes and environmental issues: A case study. *Journal of Cleaner Production, 324*, 129244. https://doi.org/10.1016/j.jclepro.2021.129244

Chen, Y., Wang, Z., & Zhong, Z. (2019). **CO_2** emissions, economic growth, renewable and non-renewable energy production and foreign trade in China. *Renewable Energy, 131*, 208-216. https://doi.org/10.1016/j.renene.2018.07.047

Debnath, K. B., Mourshed, M., & Chew, S. P. (2015). Modelling and Forecasting Energy Demand in Rural Households of Bangladesh. *Energy Procedia, 75*, 2731-2737. https://doi.org/10.1016/j.egypro.2015.07.480

Dehdar, F., Silva, N., Fuinhas, J. A., Koengkan, M., & Nazeer, N. (n.d.). The Impact of Technology and Government Policies on OECD Carbon Dioxide Emissions. *Energies*.

Engle, R. F., & Granger, C. W. (1987). Co-Integration and Error Correction: Representation, Estimation, and Testing. *Econometrica, 55*(2), 251-276. https://doi.org/10.2307/1913236

Ergun, U., & Ibrahim, A. (2013). Global Energy Prices and the Behavior of Energy Stock Price Fluctuations. *Asian Economic and Financial Review, 3*(11), 1460–1465. Retrieved from https://archive.aessweb.com/index.php/5002/article/view/1101

Ghalehkhondabi, I., Ardjmand, E., Weckman, G. R., & Young, W. A. (2017). An overview of energy demand forecasting methods published in 2005-2015. *Energy Systems, 8*, 411–447. https://doi.org/10.1007/s12667-016-0203-y

Granger, C. W., & Newbold, P. (1974). Spurious regressions in econometrics. *Journal of Econometrics, 2*(2), 111-120. https://doi.org/10.1016/0304-4076(74)90034-7

Gunatilake, H., & Roland-Holst, D. (2013). *Energy Policy Options for Sustainable Development in Bangladesh*. Mandaluyong: Asian Development Bank. Retrieved from https://www.adb.org/sites/default/files/publication/31141/ewp-359.pdf

Guo, H., Chen, Q., Xia, Q., Kang, C. Q., & Zhang, X. (2018). A monthly electricity consumption forecasting method based on vector error correction model and self-adaptive screening method. *International Journal of Electrical Power & Energy Systems, 95*, 427-439. https://doi.org/10.1016/j.ijepes.2017.09.011

IMF. (2024, March 21). *Global price of Energy index [PNRGINDEXQ]*. Retrieved from FRED, Federal Reserve Bank of St. Louis: https://fred.stlouisfed.org/series/PNRGINDEXQ

Islam, M. S. (2023, October 23). *Beyond sales gimmick: How Bangladesh can expand its green market. The Business Standard*. https://www.tbsnews.net/thoughts/beyond-sales-gimmick-how-bangladesh-can-expand-its-green-market-724954

Johansen, S. (1995). *Likelihood-Based Inference in Cointegrated Vector Autoregressive Models* (Online Edition ed.). Oxford University Press. https://doi.org/10.1093/0198774508.001.0001

Kabir, G., & Sumi, R. S. (2012). Integrating fuzzy Delphi method with artificial neural network for demand forecasting of power engineering company. *Management Science Letters, 2*, 1491–1504. https:10.5267/j.msl.2012.04.010

Kandananond, K. (2011). Forecasting Electricity Demand in Thailand with an Artificial Neural Network Approach. *Energies, 4*(8), 1246-1257. https://doi.org/10.3390/en4081246

Karanfil, F. (2008). Energy consumption and economic growth revisited: Does the size of unrecorded economy matter? *Energy Policy, 36*(8), 3029-3035. https://doi.org/10.1016/j.enpol.2008.04.002

Kavaklioglu, K. (2011). Modeling and prediction of Turkey's electricity consumption using Support Vector Regression. *Applied Energy, 88*(1), 368-375. https://doi.org/10.1016/j.apenergy.2010.07.021

Kucukali, S., & Baris, K. (2010). Turkey's short-term gross annual electricity demand forecast by fuzzy logic approach. *Energy Policy, 38*(5), 2438-2445. https://doi.org/10.1016/j.enpol.2009.12.037

Kumar , U., & Jain, V. K. (2010). Time series models (Grey-Markov, Grey Model with rolling mechanism and singular spectrum analysis) to forecast energy consumption in India. *Energy, 35*(4), 1709-1716. https://doi.org/10.1016/j.energy.2009.12.021

Kwak, Y., Seo, D., Jang, C., & Huh, J.-H. (2013). Feasibility study on a novel methodology for short-term real-time energy demand prediction using weather forecasting data. *Energy and Buildings, 55*, 250-260. https://doi.org/10.1016/j.enbuild.2012.10.041

Lee, C.-C., & Chang, C.-P. (2005). Structural breaks, energy consumption, and economic growth revisited: Evidence from Taiwan. *Energy Economics, 27*(6), 857-872. https://doi.org/10.1016/j.eneco.2005.08.003

Menyah, K., & Wolde-Rufael, Y. (2010). **CO_2** emissions, nuclear energy, renewable energy and economic growth in the US. *Energy Policy, 38*(6), 2911-2915. https://doi.org/10.1016/j.enpol.2010.01.024

Moazzem, K. G., & Khandker, A. (2023, March 13). How global energy market volatility impacted inflation in Bangladesh. *The Daily Star*. https://www.thedailystar.net/opinion/views/news/how-global-energy-market-volatility-impacted-inflation-bangladesh-3269856

Mondal, M. A., Boie, W., & Denich, M. (2010). Future demand scenarios of Bangladesh power sector. *Energy Policy, 38*(11), 7416-7426. https://doi.org/10.1016/j.enpol.2010.08.017

Montgomery, D. C., Jennings, C. L., & Kulahci, M. (2008). *Introduction to Time Series Analysis and Forecasting*. Wiley-Interscience by John Wiley & Sons. Inc. Retrieved from https://books.google.com.bd/books/about/Introduction_to_Time_Series_Analysis_and.html?id=IY6OQgAACAAJ&redir_esc=y

MoPEMR. (2023). *Integrated Energy and Power Master Plan (IEPMP) 2023*. Ministry of Power, Energy and Mineral Resources, Government of the People's Republic of Bangladesh. Retrieved from https://powerdivision.portal.gov.bd/sites/default/files/files/powerdivision.portal.gov.bd/page/4f81bf4d_1180_4c53_b27c_8fa0eb11e2c1/IEPMP%202023.pdf

Nelson, C. R., & Plosser, C. R. (1982). Trends and random walks in macroeconmic time series: Some evidence and implications. *Journal of Monetary Economics, 10*(2), 139-162. https://doi.org/10.1016/0304-3932(82)90012-5

Ozturk, I. (2010). A literature survey on energy–growth nexus. *Energy Policy, 38*(1), 340-349. https://doi.org/10.1016/j.enpol.2009.09.024

Pappas, S. S., Ekonomou, L., Karampelas, P., Karamousantas, D. C., Katsikas, S. K., Chatzarakis, G. E., & Skafidas, P. D. (2010). Electricity demand load forecasting of the Hellenic power system using an ARMA model. *Electric Power Systems Research, 80*(3), 256-264. https://doi.org/10.1016/j.epsr.2009.09.006

Paul, B. P., & Uddin, G. S. (2011). Energy and output dynamics in Bangladesh. *Energy Economics, 33*(3), 480-487. https://doi.org/10.1016/j.eneco.2010.11.011

Payne, J. E. (2009). On the dynamics of energy consumption and output in the US. *Applied Energy, 86*(4), 575-577. https://doi.org/10.1016/j.apenergy.2008.07.003

Polemis, M. L., & Dagoumas, A. S. (2013). The electricity consumption and economic growth nexus: Evidence from Greece. *Energy Policy, 62*, 798-808. https://doi.org/10.1016/j.enpol.2013.06.086

Ritchie, H., Rosado, P., & Roser, M. (2023a). *Data Page: Primary energy consumption*. (Our World in Data) Retrieved from Part of the following publication: “Energy”: https://ourworldindata.org/grapher/primary-energy-cons

Ritchie, H., Rosado, P., & Roser, M. (2023b). *Data Page: Annual CO_2 emissions*. Retrieved from CO_2 and Greenhouse Gas Emissions: https://ourworldindata.org/grapher/annual-co2-emissions-per-country

Riti, J. S., Shu, Y., Song, D., & Kamah, M. (2017). The contribution of energy use and financial development by source in climate change mitigation process: A global empirical perspective. *Journal of Cleaner Production, 148*, 882-894. https://doi.org/10.1016/j.jclepro.2017.02.037

Shahbaz, M., Tang, C. F., & Shabbir, M. S. (2011). Electricity consumption and economic growth nexus in Portugal using cointegration and causality approaches. *Energy Policy, 39*(6), 3529-3536. https://doi.org/10.1016/j.enpol.2011.03.052

Suganthi, L., & Samuel, A. A. (2012). Energy models for demand forecasting - A review. *Renewable and Sustainable Energy Reviews, 16*(2), 1223-1240. https://doi.org/10.1016/j.rser.2011.08.014

United Nations. (2022). *World Population Prospects*. Retrieved from Our World in Data: https://ourworldindata.org/explorers/population-and-demography?facet=none&country=~BGD&hideControls=false&Metric=Population&Sex=Both+sexes&Age+group=Total&Projection+Scenario=None

Wadud, Z., Dey, H. S., Kabir, M. A., & Khan, S. I. (2011). Modeling and forecasting natural gas demand in Bangladesh. *Energy Policy, 39*(11), 7372-7380. https://doi.org/10.1016/j.enpol.2011.08.066

Zhang, X.-P., & Cheng, X.-M. (2009). Energy consumption, carbon emissions, and economic growth in China. *Ecological Economics, 68*(10), 2706-2712. https://doi.org/10.1016/j.ecolecon.2009.05.011

APPENDIXES

Appendix A: Unit Root Test

Table A.1: ADF Test of Primary Energy Consumption

				Number of Observation = 47
e		Interpolated Dickey-Fuller		
	Test Statistics	1% Critical Value	5% Critical Value	10% Critical Value
Z(t)	3.088	-3.600	-2.938	-2.604
MacKinnon approximate p-value for Z(t) = 1.0000				

Source: Authors' Calculation.

Table A.2: ADF Test of First Difference of Primary Energy Consumption

				Number of Observation = 46
D.e		Interpolated Dickey-Fuller		
	Test Statistics	1% Critical Value	5% Critical Value	10% Critical Value
Z(t)	-7.200	-3.607	-2.941	-2.605
MacKinnon approximate p-value for Z(t) = 0.0000				

Source: Authors' Calculation.

Table A.3: Phillips-Perron Test for Unit Root for First Difference of Primary Energy Consumption

				Number of Observation = 46 Newey-West lags = 3
D.e		Interpolated Dickey-Fuller		
	Test Statistics	1% Critical Value	5% Critical Value	10% Critical Value
Z(rho)	-56.708	-18.628	-13.172	-10.620
Z(t)	-7.200	-3.607	-2.941	-2.605
MacKinnon approximate p-value for Z(t) = 0.0000				

Source: Authors' Calculation.

Table A.4: ADF Test of Logarithm of GDP

				Number of Observation = 47
lngdp		Interpolated Dickey-Fuller		
	Test Statistics	1% Critical Value	5% Critical Value	10% Critical Value
Z(t)	4.855	-3.600	-2.938	-2.604
MacKinnon approximate p-value for Z(t) = 1.0000				

Source: Authors' Calculation.

Table A.5: ADF Test of First Difference of Logarithm of GDP

				Number of Observation = 46
D.lngdp			Interpolated Dickey-Fuller	
	Test Statistics	1% Critical Value	5% Critical Value	10% Critical Value
Z(t)	-5.499	-3.607	-2.941	-2.605
MacKinnon approximate p-value for Z(t) = 0.0000				

Source: Authors' Calculation.

Table A.6: Phillips-Perron Test for Unit Root for First Difference of Logarithm of GDP

				Number of Observation = 46 Newey-West lags = 3
D.lngdp			Interpolated Dickey-Fuller	
	Test Statistics	1% Critical Value	5% Critical Value	10% Critical Value
Z(rho)	-47.515	-18.628	-13.172	-10.620
Z(t)	-5.799	-3.607	-2.941	-2.60
MacKinnon approximate p-value for Z(t) = 0.0000				

Source: Authors' Calculation.

Table A.7: ADF Test of Detrended Global Energy Price Index

				Number of Observation = 47
p_hat			Interpolated Dickey-Fuller	
	Test Statistics	1% Critical Value	5% Critical Value	10% Critical Value
Z(t)	4.855	-3.607	-2.941	-2.605
MacKinnon approximate p-value for Z(t) = 1.0000				

Source: Authors' Calculation.

Table A.8: ADF Test of First Difference of Detrended Global Energy Price Index

				Number of Observation = 45
D.p_hat			Interpolated Dickey-Fuller	
	Test Statistics	1% Critical Value	5% Critical Value	10% Critical Value
Z(t)	-6.752	-3.614	-2.941	-2.606
MacKinnon approximate p-value for Z(t) = 0.0000				

Source: Authors' Calculation.

Table A.9: Phillips-Perron Test for Unit Root of First Difference of Detrended Global Energy Price Index

				Number of Observation = 45
				Newey-West lags = 3
D.p_hat		Interpolated Dickey-Fuller		
	Test Statistics	1% Critical Value	5% Critical Value	10% Critical Value
Z(rho)	-44.668	-18.560	-13.140	-10.600
Z(t)	-5.799	-3.607	-2.941	-2.605
MacKinnon approximate p-value for Z(t) = 0.0000				

Source: Authors' Calculation.

Table A.10: ADF Test of Population Growth

				Number of Observation = 47
popgr		Interpolated Dickey-Fuller		
	Test Statistics	1% Critical Value	5% Critical Value	10% Critical Value
Z(t)	-0.283	-3.607	-2.941	-2.605
MacKinnon approximate p-value for Z(t) = 0.9279				

Source: Authors' Calculation.

Table A.11: ADF Test of First Difference of Population Growth

				Number of Observation = 45
D.popgr		Interpolated Dickey-Fuller		
	Test Statistics	1% Critical Value	5% Critical Value	10% Critical Value
Z(t)	-6.752	-3.614	-2.941	-2.606
MacKinnon approximate p-value for Z(t) = 0.0000				

Source: Authors' Calculation.

Table A.12: Phillips-Perron Test for Unit Root of First Difference of Population Growth

				Number of Observation = 45
				Newey-West lags = 3
D.popgr		Interpolated Dickey-Fuller		
	Test Statistics	1% Critical Value	5% Critical Value	10% Critical Value
Z(rho)	-44.668	-18.560	-13.140	-10.600
Z(t)	-5.799	-3.607	-2.941	-2.605
MacKinnon approximate p-value for Z(t) = 0.0000				

Source: Authors' Calculation.

Table A.13: ADF Test of Total CO_2 Emissions

				Number of Observation = 47
co2		Interpolated Dickey-Fuller		
	Test Statistics	1% Critical Value	5% Critical Value	10% Critical Value
Z(t)	4.855	-3.600	-2.938	-2.604
MacKinnon approximate p-value for Z(t) = 1.0000				

Source: Authors' Calculation.

Table A.14: ADF Test of First Difference of Total CO_2 Emissions

				Number of Observation = 46
D.co2		Interpolated Dickey-Fuller		
	Test Statistics	1% Critical Value	5% Critical Value	10% Critical Value
Z(t)	-5.499	-3.607	-2.941	-2.605
MacKinnon approximate p-value for Z(t) = 0.0000				

Source: Authors' Calculation.

Table A.15: Phillips-Perron Test for Unit Root of First Difference of Total CO_2 Emissions

				Number of Observation = 46 Newey-West lags = 3
D.co2		Interpolated Dickey-Fuller		
	Test Statistics	1% Critical Value	5% Critical Value	10% Critical Value
Z(rho)	-47.515	-18.628	-13.172	-10.620
Z(t)	-5.799	-3.607	-2.941	-2.605
MacKinnon approximate p-value for Z(t) = 0.0000				

Source: Authors' Calculation.

Appendix B: Trend Analysis

Table B.1: Regression Result of Bivariate Regression between Time and Global Energy Price Index

VARIABLES	(R1) e	(R2) lngdp	(R3) co2	(R4) popgr	(R5) p
t	9.797***	0.0492***	1.978***	-0.0375***	4.143***
	(0.501)	(0.000738)	(0.104)	(0.00239)	(0.428)
Constant	-19,404***	-73.08***	-3,917***	76.66***	-8,192***
	(1,001)	(1.475)	(208.8)	(4.777)	(855.3)
Observations	48	48	48	47	47
R-squared	0.893	0.990	0.886	0.845	0.675
		Standard errors in parentheses *** p<0.01, ** p<0.05, * p<0.1			

Source: Authors' Calculation.

Note: The table above summarises the results of bivariate regression analyses between time and various variables. R1 denotes the regression analysis between primary energy consumption (e) and time. Likewise, regressions R2, R3, R4, and R5 correspond to analyses between the logarithm of GDP (lngdp) and time, total CO_2 emissions (co2) and time, population growth rate (popgr) and time, and the Global Energy Price Index (p) and time, respectively.

Appendix C: Selection Order Criteria

Table C.1: Selection Order Criteria of VAR using Primary Energy Consumption (e) and Logarithm of GDP (lngdp)

lags	LL	LR	df	p	FPE	AIC	HQIC	SBIC
0	-255.56				416.405	11.7074	11.7375	11.7885
1	-33.533	444.06*	4	0	0.02068	1.79694	1.8872*	2.04024*
2	-28.839	9.3873	4	0.052	0.02007*	1.7654*	1.91579	2.17091
3	-26.057	5.5651	4	0.234	0.02129	1.82075	2.03128	2.38845
4	-22.515	7.083	4	0.132	0.02187	1.84159	2.11227	2.57149

Source: Authors' Calculation.

Table C.2: Selection Order Criteria of VAR using Primary Energy Consumption (e), Logarithm of GDP (lngdp) and total CO_2 emissions (co2)

lags	LL	LR	df	p	FPE	AIC	HQIC	SBIC
0	-335.31				957.442	15.3779	15.423	15.4995
1	-110.08	450.46	9	0	0.05167	5.54918	5.72963*	6.03578*
2	-99.206	21.752	9	0.01	0.04776	5.4639	5.77969	6.31544
3	-95.09	8.2318	9	0.511	0.0606	5.68591	6.13704	6.9024
4	-74.313	41.555*	9	0	.036567*	5.15057*	5.73704	6.73201

Source: Authors' Calculation.

Table C.3: Selection Order Criteria of VAR using Primary Energy Consumption (e), Logarithm of GDP (lngdp), total CO_2 emissions (co2) and population growth rate (popgr)

lags	LL	LR	df	p	FPE	AIC	HQIC	SBIC
0	-312.53				29.0972	14.7221	14.7825	14.886
1	-67.069	490.91	16	0	0.00068	4.04972	4.3518	4.86888
2	-36.064	62.01	16	0	.000344*	3.35182	3.89556*	4.82631*
3	-29.707	12.714	16	0.694	0.00057	3.80033	4.58574	5.93015
4	-0.7354	57.943*	16	0	0.00035	3.19699*	4.22407	5.98215

Source: Authors' Calculation.

Table C.4: Selection Order Criteria of VAR using Primary Energy Consumption (e), Logarithm of GDP (lngdp), total CO_2 emissions (co2), population growth rate (popgr) and detrended Global Energy Price Index (p_hat)

lags	LL	LR	df	p	FPE	AIC	HQIC	SBIC
0	-511.21				32601.1	24.5814	24.6573	24.7883
1	-253.29	515.83	25	0	0.5019	13.4902	13.9451	14.7314
2	-202.87	100.86	25	0	0.15761	12.2793	13.1133*	14.5548*
3	-186	33.731	25	0.114	0.26699	12.6666	13.8798	15.9765
4	-138.6	94.791*	25	0	.12293*	11.6002*	13.1925	15.9444

Source: Authors' Calculation.

Appendix D: Johansen Cointegration Test

Table D.1: Johansen Cointegration Test Results for Primary Energy Consumption and Logarithm of GDP

Maximum Rank	Parms	LL	Eigenvalues	Trace Statistic	5% Critical Value
0	6	-46.844	-	28.0651	15.41
1	9	-33.06	0.45081	0.4970*	3.76
2	10	-32.811	0.01075	-	-

Source: Authors' Calculation.

Table D.2: Johansen Cointegration Test Results for Primary Energy Consumption, Logarithm of GDP and Total CO_2 emissions

Maximum Rank	Parms	LL	Eigenvalues	Trace Statistic	5% Critical Value
0	12	-127.85	-	43.8203	29.68
1	17	-111.19	0.51538	10.4981*	15.41
2	20	-106.11	0.1984	0.3255	3.76
3	21	-105.94	0.00705	-	-

Source: Authors' Calculation.

Table D.3: Johansen Cointegration Test Results for Primary Energy Consumption, Logarithm of GDP and Total CO_2 emissions

Maximum Rank	Parms	LL	Eigenvalues	Trace Statistic	5% Critical Value
0	20	-75.612	-	69.0004	47.21
1	27	-55.357	0.59352	28.4902*	29.68
2	32	-46.198	0.3344	10.1723	15.41
3	35	-41.215	0.19866	0.2059	3.76
4	36	-41.112	0.00457	-	-

Source: Authors' Calculation.

Table D.4: Johansen Cointegration Test Results for Primary Energy Consumption, Logarithm of GDP and Total CO_2 emissions

Maximum Rank	Parms	LL	Eigenvalues	Trace Statistic	5% Critical Value
0	30	-269.43	.	100.394	68.52
1	39	-246.83	0.64198	55.1996	47.21
2	46	-233.5	0.45435	28.5454*	29.68
3	51	-222.98	0.38006	7.5075	15.41
4	54	-219.27	0.15528	0.0823	3.76
5	55	-219.23	0.00187	-	-

Source: Authors' Calculation.

Appendix E: Short Run Result of Vector Error Correction Model

Table E.1: Results from Vector Error Correction Model for Scenario 1 (Variables: Primary Energy Consumption and Logarithm of GDP)

VARIABLES	(1) D_e	(2) D_lngdp
L._ce1	-0.100**	-0.000161***
	(0.0508)	(4.74e-05)
LD.e	-0.429***	0.000204
	(0.147)	(0.000137)
L2D.e	-0.121	0.000268*
	(0.154)	(0.000144)
L3D.e	0.160	0.000459***
	(0.163)	(0.000153)
L4D.e	0.746***	0.000572***
	(0.167)	(0.000156)
LD.lngdp	1.971	-0.296*
	(165.8)	(0.155)
L2D.lngdp	41.54	-0.0511
	(143.8)	(0.134)
L3D.lngdp	89.14	0.196
	(141.9)	(0.133)
L4D.lngdp	46.11	-0.281**
	(146.5)	(0.137)
Constant	-9.30e-05	0.0579***
	(12.84)	(0.0120)
Observations	43	43

Standard errors in parentheses
*** p<0.01, ** p<0.05, * p<0.1

Source: Authors' Calculation.

Table E.2: Results from Vector Error Correction Model for Scenario 2 (Variables: Primary Energy Consumption, Logarithm of GDP and Total CO_2 Emissions)

VARIABLES	(1) D_e	(2) D_lngdp	(3) D_co2
L._ce1	0.578***	0.000438**	0.176***
	(0.220)	(0.000209)	(0.0369)
LD.e	-0.669*	2.46e-05	-0.0865
	(0.379)	(0.000359)	(0.0635)
L2D.e	-0.361	6.92e-05	-0.0942
	(0.358)	(0.000339)	(0.0598)

(Table E.2 contd.)

(Table E.2 contd.)

VARIABLES	(1) D_e	(2) D_lngdp	(3) D_co2
L3D.e	-0.0538	0.000178	-0.128***
	(0.296)	(0.000280)	(0.0495)
LD.lngdp	116.9	-0.187	23.74
	(162.0)	(0.153)	(27.08)
L2D.lngdp	131.5	0.0319	18.92
	(170.7)	(0.162)	(28.55)
L3D.lngdp	152.4	0.356**	31.31
	(162.8)	(0.154)	(27.22)
LD.co2	-0.924	-0.00150	-0.585**
	(1.428)	(0.00135)	(0.239)
L2D.co2	-1.710	-0.00168	-0.400
	(1.607)	(0.00152)	(0.269)
L3D.co2	-1.845	-0.00141	-0.370
	(1.501)	(0.00142)	(0.251)
Constant	-0.302	0.0382***	0.991
	(15.30)	(0.0145)	(2.559)
Observations	44	44	44

Standard errors in parentheses
*** p<0.01, ** p<0.05, * p<0.1

Source: Authors' Calculation.

Table E.3: Results from Vector Error Correction Model for Scenario 3 (Variables: Primary Energy Consumption, Logarithm of GDP, Total CO_2 Emissions and Population Growth Rate)

VARIABLES	(1) D_e	(2) D_lngdp	(3) D_co2	(4) D_popgr
L._ce1	0.270**	0.000523***	0.0676***	0.00201***
	(0.113)	(0.000109)	(0.0223)	(0.000725)
LD.e	-0.149	3.40e-05	0.0826*	0.000669
	(0.254)	(0.000243)	(0.0500)	(0.00162)
LD.lngdp	207.7	-0.187	45.36	-3.060***
	(164.0)	(0.157)	(32.29)	(1.048)
LD.co2	-1.415	-0.000782	-0.833***	0.00251
	(1.022)	(0.000978)	(0.201)	(0.00653)
LD.popgr	5.143	0.0135	0.679	0.621***
	(18.02)	(0.0172)	(3.549)	(0.115)
Constant	0.0922	0.0522***	-0.372	0.0927**
	(7.196)	(0.00689)	(1.417)	(0.0460)
Observations	45	45	45	45

Standard errors in parentheses
*** p<0.01, ** p<0.05, * p<0.1

Source: Authors' Calculation.

Table E.4: Results from Vector Error Correction Model for Scenario 4 (Variables: Primary Energy Consumption, Logarithm of GDP, Total CO_2 Emissions, Population Growth Rate and Global Energy Price Index)

VARIABLES	(1) D_e	(2) D_lngdp	(3) D_co2	(4) D_popgr	(5) D_p_hat
L._ce1	1.186***	0.000831**	0.323***	-0.00171	-2.367**
	(0.398)	(0.000410)	(0.0751)	(0.00291)	(0.964)
L._ce2	-5.594	-0.0179***	-0.690	-0.0809**	-30.49**
	(5.052)	(0.00520)	(0.953)	(0.0369)	(12.23)
LD.e	-0.616*	-9.01e-05	-0.0676	0.00209	0.633
	(0.352)	(0.000363)	(0.0664)	(0.00257)	(0.852)
LD.lngdp	-56.55	-0.369**	-8.303	-1.990*	388.6
	(160.5)	(0.165)	(30.26)	(1.172)	(388.5)
LD.co2	0.681	-0.000124	-0.207	-0.00471	-7.405**
	(1.358)	(0.00140)	(0.256)	(0.00992)	(3.287)
LD.popgr	9.205	0.0154	0.953	0.588***	28.12
	(16.25)	(0.0167)	(3.064)	(0.119)	(39.33)
LD.p_hat	0.118*	9.47e-05	0.0128	-0.000780	-0.154
	(0.0706)	(7.28e-05)	(0.0133)	(0.000516)	(0.171)
Constant	0.177	0.0486***	-0.763	0.0446	-0.0153
	(6.276)	(0.00647)	(1.183)	(0.0458)	(15.19)
Observations	44	44	44	44	44

Standard errors in parentheses
*** p<0.01, ** p<0.05, * p<0.1

Source: Authors' Calculation.

Appendix F: Long Run Result of Vector Error Correction Model

Table F.1: Johansen Cointegration Test Results: Normalised Cointegrating Vectors Indicating Long-Term Relationships Between Primary Energy Consumption and Logarithm of GDP (Scenario-1)

beta	Coefficient	Standard Error	z	P>|z|	[95% Confidence Interval]	
			_ce1			
e	1	-	-	-	-	-
lngdp	-245.4225	46.53912	-5.27	0.00	-336.6375	-154.2075
_cons	6016.297	-	-	-	-	-

Source: Authors' Calculation.

Table F.2: Johansen Cointegration Test Results: Normalised Cointegrating Vectors Indicating Long-Term Relationships Among Primary Energy Consumption, Logarithm of GDP and Total CO_2 Emissions (Scenario-2)

beta	**Coefficient**	**Standard Error**	**z**	**P>|z|**	**[95% Confidence Interval]**	
			_ce1			
e	1	-	-	-	-	-
lngdp	14.2268	10.4739	1.36	0.174	-6.3016	34.7551
_cons	-4.2621	0.32774	-13	0	-4.9044	-3.6197
_cons	-363.36	-	-	-	-	-

Source: Authors' Calculation.

Table F.3: Johansen Cointegration Test Results: Normalised Cointegrating Vectors Indicating Long-Term Relationships Among Primary Energy Consumption, Logarithm of GDP, Total CO_2 Emissions and Population Growth Rate (Scenario-3)

beta	Coefficient	Standard Error	z	P>|z|	[95% Confidence Interval]	
			_ce1			
e	1	-	-	-	-	-
lngdp	-58.714	21.8707	-2.68	0.007	-101.58	-15.848
co2	-3.8746	0.40003	-9.69	0	-4.6586	-3.0906
popgr	-54.122	11.0304	-4.91	0	-75.742	-32.503
_cons	1553.75	-	-	-	-	-

Source: Authors' Calculation.

Table F.4: Johansen Cointegration Test Results: Normalised Cointegrating Vectors Indicating Long-Term Relationships Among Primary Energy Consumption, Logarithm of GDP, Total CO_2 Emissions, Population Growth Rate and Global Energy Price Index (Scenario-4)

beta	Coefficient	Standard Error	z	P>|z|	[95% Confidence Interval]	
			_ce1			
e	1	-	-	-	-	-
lngdp	0	(omitted)				
co2	-4.70719	0.0591	-79.65	0	-4.823	-4.5914
popgr	2.66685	2.8055	0.95	0.342	-2.8318	8.16553
p_hat	0.12027	0.022	5.47	0	0.07714	0.16339
_cons	-0.87598	-	-	-	-	-
			_ce2			
e	-1.39E-17	-	-	-	-	-
lngdp	1	-	-	-	-	-
co2	-0.01715	0.00459	-3.74	0	-0.0261	-0.0082
popgr	1.23043	0.21778	5.65	0	0.80359	1.65727
p_hat	0.0016	0.00171	0.94	0.349	-0.0017	0.00495
_cons	-27.3943	-	-	-	-	-

Source: Authors' Calculation.

Appendix G: Stability Test of Vector Error Correction Models

Table G.1: Stability Test of VECM (Variables: Primary Energy Consumption and Logarithm of GDP at Lag = 2)

Eigenvalue	Modulus
1.00369	1.00369
1	1
-0.3792	0.3792
-0.2961645	0.2961645

Source: Authors' Calculation.

Table G.2: Stability Test of VECM (Variables: Primary Energy Consumption and Logarithm of GDP at Lag = 5)

Eigenvalue		Modulus
1		1
-0.9793825		0.979382
-0.1824139	+ 0.9411086i	0.958624
-0.1824139	- 0.9411086i	0.958624
0.9426355	+ 0.1088832i	0.948903
0.9426355	- 0.1088832i	0.948903
-0.5900422	+ 0.6060891i	0.845869
-0.5900422	- 0.6060891i	0.845869
0.4264461	+ 0.4741149i	0.637684
0.4264461	- 0.4741149i	0.637684

Source: Authors' Calculation.

Table G.3: Stability Test of VECM (Variables: Primary Energy Consumption, Logarithm of GDP and Total CO_2 Emissions)

Eigenvalue		Modulus
1		1
1		1
0.983572		0.983572
-0.97735		0.977353
-0.01683	+ .9126926i	0.912848
-0.01683	- .9126926i	0.912848
-0.42939	+ .6075207i	0.743945
-0.42939	- .6075207i	0.743945
0.700416		0.700416
-0.41013	+ .5038286i	0.649655
-0.41013	- .5038286i	0.649655
0.397933		0.397933

Source: Authors' Calculation.

Table G.4: Stability Test of VECM (Variables: Primary Energy Consumption, Logarithm of GDP, Total CO_2 Emissions and Population Growth Rate)

Eigenvalue		Modulus
1		1
1		1
1		1
0.823128		0.823128
0.658452		0.658452
-.5369267		0.536927
-0.3117453	+ .09054907i	0.324629
-0.3117453	- .09054907i	0.324629

Source: Authors' Calculation.

Table G.5: Stability Test of VECM (Variables: Primary Energy Consumption, Logarithm of GDP, Total CO_2 Emissions, Population Growth Rate and Global Energy Price Index)

Eigenvalue		Modulus
1		1
1		1
1		1
0.923628		0.923628
0.63602		0.63602
-0.537659		0.537659
-0.385	+ .1371622i	0.385
-0.385	- .1371622i	0.385
0.313534	+ .3029265i	0.313534
0.313534	- .3029265i	0.313534

Source: Authors' Calculation.

Appendix H: Forecast of Energy Consumption by Scenarios

Table H.1: Forecast of Scenario 1 (Primary Energy Consumption and Logarithm of GDP)

Year	Primary Energy Consumption (Tw-H)	GDP (Billion 2015 constant USD)	Year	Primary Energy Consumption (Tw-H)	GDP (Billion 2015 constant USD)
2019	483	257.87	2035	649	582.29
2020	457	266.76	2036	657	613.40
2021	479	285.27	2037	686	646.79
2022	499	305.52	2038	674	675.14
2023	529	319.13	2039	696	713.03
2024	504	333.81	2040	706	751.39
2025	541	354.56	2041	727	790.29
2026	554	371.99	2042	718	827.30
2027	569	391.38	2043	748	876.83
2028	554	408.63	2044	754	921.73

(Table H.1 contd.)

(Table H.1 contd.)

Year	Primary Energy Consumption (Tw-H)	GDP (Billion 2015 constant USD)	Year	Primary Energy Consumption (Tw-H)	GDP (Billion 2015 constant USD)
2029	596	434.53	2045	770	969.36
2030	597	455.35	2046	769	1019.48
2031	607	476.02	2047	800	1080.20
2032	605	501.29	2048	801	1133.88
2033	644	530.91	2049	817	1194.96
2034	634	552.87	2050	823	1260.05

Source: Authors' Calculation.

Table H.2: Forecast of Scenario 2 (Primary Energy Consumption, Logarithm of GDP and Total CO_2 Emission)

Year	Primary Energy Consumption (Tw-H)	GDP (Billion 2015 constant USD)	Total CO_2 Emission (million tonnes)	Year	Primary Energy Consumption (Tw-H)	GDP (Billion 2015 constant USD)	Total CO_2 Emission (million tonnes)
2019	483	257.87	101	2035	783	699.35	174
2020	457	266.76	94	2036	786	739.88	172
2021	479	285.27	99	2037	818	795.50	181
2022	499	305.52	102	2038	834	847.51	183
2023	546	326.68	119	2039	870	910.69	194
2024	534	341.48	112	2040	877	965.92	194
2025	559	366.18	120	2041	910	1039.06	203
2026	577	389.61	122	2042	925	1107.63	205
2027	620	418.58	136	2043	960	1190.70	215
2028	614	439.55	132	2044	970	1265.65	216
2029	643	471.64	140	2045	1003	1362.02	225
2030	660	502.52	141	2046	1019	1452.96	227
2031	699	539.54	154	2047	1053	1562.65	237
2032	699	568.90	152	2048	1065	1664.04	238
2033	730	611.38	160	2049	1098	1791.36	248
2034	746	651.09	162	2050	1115	1912.56	250

Source: Authors' Calculation.

Table H.3: Forecast of Scenario 3 (Primary Energy Consumption, Logarithm of GDP, Total CO_2 Emission and Population Growth Rate)

Year	Primary Energy Consumption (Tw-H)	GDP (Billion 2015 constant USD)	Total CO_2 Emission (in million tonnes)	Population Growth Rate
2019	483	257.87	101	1.12
2020	457	266.76	94	1.15
2021	479	285.27	99	1.16
2022	499	305.52	102	1.08
2023	517	324.50	107	1.029
2024	533	345.02	110	1.021
2025	551	367.35	114	1.032
2026	567	390.47	117	1.050
2027	584	415.00	121	1.072
2028	600	440.55	125	1.092
2029	616	467.37	128	1.110
2030	631	495.39	131	1.125
2031	646	524.75	134	1.136
2032	660	555.49	137	1.143
2033	674	587.72	140	1.147
2034	688	621.54	143	1.148
2035	701	657.04	146	1.147
2036	715	694.35	149	1.143
2037	728	733.58	152	1.138
2038	741	774.84	155	1.130
2039	754	818.27	157	1.122
2040	767	864.00	160	1.112
2041	780	912.16	163	1.101
2042	792	962.90	165	1.090
2043	805	1016.37	168	1.078
2044	818	1072.74	171	1.065
2045	830	1132.15	173	1.052
2046	843	1194.80	176	1.038
2047	855	1260.87	179	1.024
2048	868	1330.54	181	1.010
2049	881	1404.02	184	0.996
2050	893	1481.53	187	0.982

Source: Authors' Calculation.

Table H.4: Forecast of Scenario 4 (Primary Energy Consumption, Logarithm of GDP, Total CO_2 Emission, Population Growth Rate and Detrended Global Energy Price Index)

Year	Primary Energy Consumption (Tw-H)	GDP (Billion 2015 constant USD)	Total CO_2 Emission (in million tonnes)	Population Growth Rate	Detrended Global Energy Price Index[7]
2019	483	257.87	101	1.12	-42.99
2020	457	266.76	94	1.15	-84.72
2021	479	285.27	99	1.16	2.52
2022	499	305.52	102	1.08	-9.94
2023	520	324.56	107	1.093	-6.34
2024	540	346.13	110	1.100	-6.68
2025	559	369.23	115	1.121	-4.77
2026	579	393.74	119	1.142	-5.71
2027	598	419.81	123	1.167	-6.58
2028	618	447.38	127	1.191	-8.18
2029	637	476.63	131	1.215	-9.72
2030	655	507.57	135	1.238	-11.49
2031	674	540.32	139	1.260	-13.23
2032	692	574.98	143	1.280	-15.02
2033	711	611.65	147	1.299	-16.78
2034	728	650.45	151	1.317	-18.53
2035	746	691.51	155	1.334	-20.25
2036	764	734.94	158	1.349	-21.94
2037	781	780.91	162	1.363	-23.60
2038	798	829.54	166	1.376	-25.24
2039	815	881.01	169	1.388	-26.84
2040	832	935.48	173	1.399	-28.41
2041	849	993.13	176	1.409	-29.96
2042	866	1054.14	180	1.419	-31.48
2043	882	1118.72	183	1.427	-32.98
2044	899	1187.08	187	1.435	-34.46
2045	915	1259.43	190	1.443	-35.92
2046	932	1336.03	194	1.449	-37.36
2047	948	1417.11	197	1.456	-38.79
2048	964	1502.95	201	1.461	-40.20
2049	980	1593.82	204	1.467	-41.59
2050	996	1690.04	207	1.471	-42.97

Source: Authors' Calculation.

[7]The negative price index does not constitute a negative energy price in future because both theoretically and realistically, a negative price is not possible. Since this variable is in a detrended form of the original variable, the negative value of detrended version constitutes a future downward pressure of price from the non-trend component of the price.

Recent CPD Working Papers

cpd.org.bd cpd.org.bd cpd_bangladesh CPDBangladesh

CENTRE FOR POLICY DIALOGUE

House 40/C, Road 11 (new)
Dhanmondi, Dhaka 1209, Bangladesh
Telephone: (+88 02) 55001185, 55001990, 58156983
Fax: (+88 02) 48110414
E-mail: info@cpd.org.bd
Website: www.cpd.org.bd