

Technological Innovation and Greener Energy Technology Adoption: Do Socioeconomic Conditions Make a Difference

Malin Song¹, Umer Shahzad², Peter Ractham, and Shanky Goyal³

Abstract—Industrialized countries and environmental protection agencies urge greener energy technology adoption and improvement in technological innovation. In this regard, the primary factor of greener energy adoption could be the budget allocated for renewable energy R&D, technological innovation, and socioeconomic conditions. The prime objective of this study is to explore the role of R&D for renewable energy adoption while considering economic and social factors. The present study analyzed quarterly data for Australia covering the period of 1994Q1–2019Q4. Furthermore, in this article, we employ the least absolute shrinkage and selection operator algorithm, ARDL bound testing, and a dynamic ARDL approach for a comprehensive empirical analysis. Empirical estimates reveal that R&D budgets for renewable energy, energy efficiency, and science and technology significantly promote greener energy adoption in the short term. However, the impact of the R&D budget on energy efficiency is positive in the long term. Technological innovation and economic growth are positively associated with green energy generation. From a policy perspective, an increase in budget allocation for R&D in renewables, energy efficiency, and technological innovation might act as a policy factor to bring environmental and economic sustainability.

Index Terms—Australia, greener energy, R&D budgets, socioeconomic conditions (SECs), technological adoption, technological innovation.

NOMENCLATURE

ARDL	Autoregressive dynamic lag regression.
BTS	Be the story.
DFGLS	Dickey–Fuller generalized least square.
EC	Economic complexity.
ECM	Error correction model.
ECT	Error correction term.

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EE	Energy efficiency.
GDP	Gross domestic product.
IEA	International Energy Agency.
IRENA	International Renewable Energy Agency.
OECD	Organization for Economic Cooperation and Development.
R&D	Research and development.
RDBCST	Research and development budget for science and technologies.
RDBEF	Research and development budgets for energy efficiency.
RDBRE	Research and development budgets for renewable energy.
RE	Renewable energy.
REC	Renewable energy generation.
SEC	Socioeconomic condition.
ZA	Zivot–Andrews

I. INTRODUCTION

A. Study Background

CLIMATE change has increasingly led to the developing of low-carbon and cost-efficient technologies that will significantly promote green economies and reduce pollution emissions [1]. The COP-21 declared that “to maintain the global temperature below the critical point of 20 °C, RE can meaningfully improve environmental concerns.” This is one of the most vital factors for the development that will enhance living standards. RE encourages technological advancement, innovation, and economic development for environmental and economic sustainability. In addition, the scientific studies have emphasized increasing the RE R&D for economic and environmental sustainability [2], [3]. Greener energy generation has increased over time, owing to growing environmental concerns because they boost technological innovation for low-carbon machinery and lead to enhanced societal and ecological conditions for economic development [4], [5]. The increase in RE consumption has transformed international markets since the global energy crisis, as it helps to encourage economic growth while reducing CO₂ emissions [6]. Since greener energy plays a significant part in managing environmental concerns and climate change challenges. Hence, the greener energy sources are perceived as highly responsive to the overall energy policy guidelines and environmental, social, and economic objectives [7]. Therefore, it can be perceived that the ultimate reason for utilizing renewable sources is to combat the environmental externalities and maintain the economic progress. However, the greener energy

sources are significant for the earth's ecosystem and have vast sources, unlike fossil fuels. Fossil fuels are depleted over time, while greener energy is considered a long-term replacement for the future of the world, especially concerning climate change and carbon abatement [8]. Over the past few years, developed economies have focused on producing greener energy sources owing to the environmental regulations and government control. For instance, Norway produces approximately 98% of its energy, Brazil utilizes 84% of its energy, and New Zealand utilizes 80% of its energy from renewable sources [9].

Energy-efficient technologies have made dramatic advances over the past few decades. The European Commission's long-term strategy (2050) advises accelerating R&D and technological innovation for sustainability. The commission's prime objective is to enhance the role of R&D by investing its GDP in R&D [4]. The transition from the conventional to modern RE technologies and development requires enormous investment projects and financial budgets for research and innovation for green technologies. Amplified budgets for low-carbon technologies could encourage innovation, economic growth, output efficiency, and societal transitions. However, along with greater economic progress, increased competition creates new challenges for development. Therefore, environmental economists have proposed three-dimensional strategies to achieve development goals. Globally, countries have also focused on decarbonizing their economies for ecological sustainability [10], [11]. Several emerging economies (Brazil, India, China, Indonesia, Turkey, and the Philippines) actively generate greener energy.

Due to the ongoing developments in climate change challenges, e.g., COP 27, the EE, technological innovation, and greener energy sources are in debate to fight environmental externalities. Environmental economics and policymakers consider greener energy, EE, and greener technology as a way to achieve economic sustainability [12], [13]. The increasing efforts of international organizations to achieve climate change goals (2030) have led to an increase in R&D funding for renewable and energy-efficient sources, which is ultimately proportional to a decrease in environmental deterioration [14].

B. Stylized Facts of Australia

Australia is a technologically advanced economy with several research centers and ongoing research activities. Additionally, Australia's sunshine, powerful winds, and outstanding expertise make it an ideal RE exporter in a low-carbon environment. Similarly, solar energy has become its primary RE source. According to IRENA, approximately 270 GW of global RE was added in 2020, surpassing the previous year's (2019) records, in which Australia's growth outperformed the world [1]. Moreover, the growth in RE has been considerable, and it is expected that Australia will achieve its 50% renewable target by 2025, reducing greenhouse emissions to below 2005 levels by 2030. In addition, ARENA has supported many projects with enormous funding to enhance the competitiveness and supply of renewable technologies in the Australian RE industry [15]. Among these technologies, solar photovoltaic is the fastest-growing renewable energy technology. In the extant literature, several studies have examined their economic and environmental practicability and report that RE sources are beneficial for mitigating climate change at the global level.

According to statistics from the Australian government [16], RE generation, especially electricity generation, has doubled

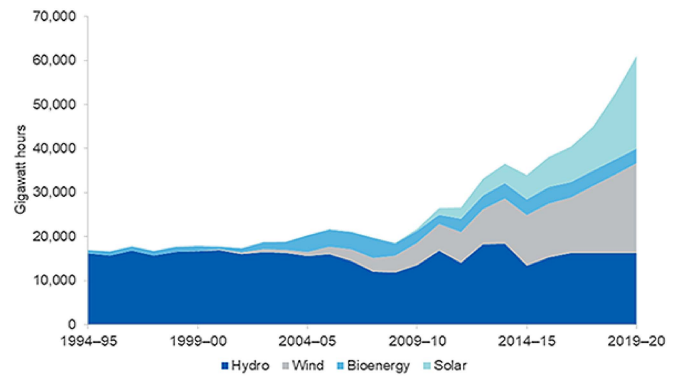


Fig. 1. Australian electricity generation from renewable sources. Source: Australian Electricity Energy Statistics (2021).

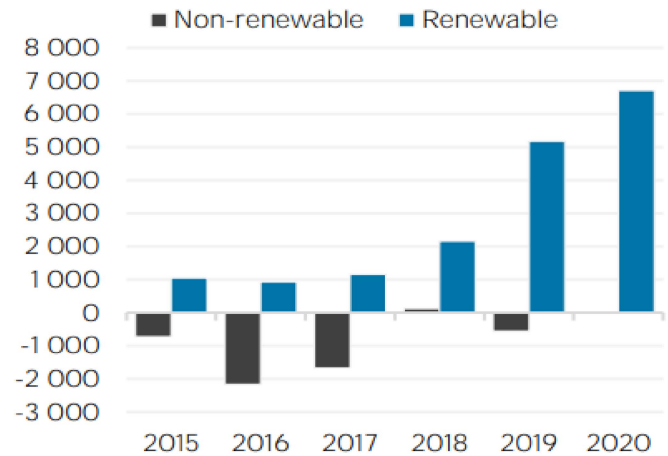


Fig. 2. Renewable and nonrenewable capacity share of Australia. Source: International Renewable Energy Agency (2021).

over the past decade. In 2020, almost 24% of electricity generation was from RE sources, the highest to date, while 21% was chronicled in 2019. This target was achieved by increasing solar installations in the country, confirming Australia's position of the RE leader in the world. Regarding innovation, the Australian Bureau of Statistics declared that 52% of businesses across the country reported innovation activity over two years before 2021 [16]. The R&D expenses were \$3618 m for 2020 and 2021, and with \$288 m for 2018 and 2019. The increasing trend representation of electricity generation from green energy resources is shown in Fig. 1. Fig. 2 shows the renewable and non-RE net capacity change over the years, indicating that the transition to renewables is gaining pace.

C. Theoretical Linkages and Study Contribution

The evolution from nonrenewable to renewable sources requires massive R&D and technological innovation [17]. Considerable research evidence, theoretical or empirical, emphasizes the importance of R&D budgets. R&D expenditure is an essential component of technological advancements and the adoption of green technologies [18]. Freimane and Bălița [19] stated that "to achieve long-term economic growth, investment in R&D is imperative [19]. Investment in the R&D budget is directly proportional to technological advancement and a country's overall productivity. This is because R&D positively contributes

to RE progression [20]. According to Romer, technological change originates from international investment decisions. In a recent study, Liu et al. [22] argued that the R&D of industrial technologies is vital for risk preferences [21], [22].

Given the above discussion, the current study aims to accomplish two objectives. The primary objective of this research is to examine the role of different types of RDBRE to draw novel implications for greener technology adoption. The second aim of this study is to analyze the influence of socioeconomic conditions (SECs) and EC on RE generation in Australia (as a sample of a developed country). In doing so, the study has drawn some novel conclusions and policy-based implications in context of R&D budgets, technological advancements, and greener energy transformation. From a policy perspective, Australia is a leading economy in technological advancement and spends huge funds to fight climate change externalities. During recent decades, significant R&D budgets were allocated to increase the share of greener energy, EE, and technological advancements. Yet, Australia still lacks in greener energy generation and EE. As a matter of fact, Australia is still facing energy issues due to unreliable and inefficient coal-fired power stations, electricity prices, coal power generation, and natural gas prices. Against this backdrop, the current study attempts to draw novel implications apropos RE generation and R&D budgets. From a logical perspective, the study analyzes if Australia's R&D budgets are being utilized for generating RE, including greener energy technologies and equipment. In addition, the current study considers socioeconomic changes and technological advancements as key policy variables for greener growth. This is justified by the fact that RE generation largely depends on the income level, poverty, consumer confidence, unemployment, and technological capacity of any country. In doing so, this research reported eye-catching conclusions and policies concerning the RE generation challenges in Australia.

This study contributes to the existing literature in three directions. First, the on-hand research determines the role of three different types of R&D budgets for greener energy generation. The explanatory factor of the R&D budget is measured in three models: R&D for RE, R&D for EE, and R&D for technologies, which is a new input in the prevailing empirical literature. The dominant research has mainly focused on the technology, regulations, and other determinants of environmental quality [17], [18]. The impact of RDBRE has been overlooked. However, it is imperative to consider and explore the impact of allocated budgeted funds on RE. Second, this study empirically analyzes the impacts of SECs, technological innovation, and EC on greener energy adaption for the Australian economy. SECs are defined as poverty, unemployment, and consumer confidence, as per the ICRG definitions. Theoretically, residents may not be inclined toward buying and using the latest technologies and renewable sources if there is more poverty and less consumer confidence. Therefore, the current study explores the relationship between SECs and greener energy generation in Australia to propose novel solutions and policy implications. Third, the current research reports novel policies and solutions regarding greener energy adoption and sustainable development. The existing literature has ignored such aspects of carbon neutrality and sustainability. The transition from nonrenewable to greener energy requires enormous investment and potential. Therefore, examining this scenario for policy planning and implementation is vital. The linkages between R&D budgets and REs allow us

to provide future recommendations for other developed-country studies and practical implications.

The rest of this article is organized as follows. Section II presents the literature review. Section III explains the data and methodology. Section IV indicates the empirical results. Section V discusses the relevance of the findings and policies to the sustainable development goals. Finally, Section VI concludes this article.

II. LITERATURE REVIEW AND RESEARCH GAP

Literature on R&D, technological advancements, and concurrent socioeconomic issues is scarce. However, the Section II-A elaborates on the extant literature according to research needs. The following sections elucidate the relevant associations and aspects of the variables under consideration.

A. R&D Budgets and RE

The OECD report states that investment in R&D (budgets/expenditures) is systematic creative work that increases knowledge, which is ultimately incorporated into the invention and innovation of new technologies. Countries that capitalize on more research and innovation perform better in terms of socioeconomic growth and enhance research innovation by investing their GDP in R&D that have better living standards [4], [11], [23]. However, the amount of investment and opportunities vary across countries, regions, and sectors because each country, region, or sector have a different potential and needs for development. Wang et al. [24] examined the empirical relationship between economic growth and R&D for 23 OECD countries from 1991 to 2006. The results show a strong positive impact of R&D spending on GDP per capita [24]. International energy organizations and commissions aim to increase the R&D of RE and transition toward greener energy for environmental and economic sustainability. In addition to those mentioned earlier, EC can be a policy factor for cleaner and greener energy promotion. RE is essential for zero carbon emissions; nevertheless, EC can help reduce the impact of economic activities to mitigate environmental concerns in OECD economies [25]. In a more recent study, Ślusarczyk et al. [26] observed significant associations between economic growth and RE consumption in Poland. In a recent study, Mele et al. [66] highlighted the fact that environment-related innovations are linked to recycled waste and income levels in Korea. International organization members, such as IEA, spent billions of funds on public sector R&D. IEA revealed the significance of R&D budgets for attaining energy independence for economic benefits. Chachuli et al. [29] investigated the performance of R&D activities in RE resources for the Malaysian economy from 2012 to 2017 (solar, biomass, minihydro, and wind) [28], [29]. The findings indicate that mini-hydropower is an efficient resource (RE), although limited R&D activities are in contrast to the other mentioned resources.

B. RE, EE, and Environmental Technologies

The literature on RE and EE is scarce, but a few related research studies are briefly discussed in this section. Many researchers and policymakers regard EE as a minimum-cost strategy for resource-sufficiency needs. Research on energy-efficient technologies is essential for reducing environmental

concerns and enhancing socioeconomic development. EE and greener energy are necessary for energy transition and conservation practices [30]. Akram et al. [31] investigated the irregular effects of RE and EE on carbon dioxide emissions. However, both are separate areas of technological development and policy implications [32].

Similarly, Vine stated that the landscape of EE program planners has varied since the energy crisis began [33]. The policymakers and experts widened the scope for integrating efficiency programs for energy to reduce dependence on greener sources and to create efficient technologies for carbon mitigation. More recently, Magazzino et al. [6] reported that technological innovation and human capital are conducive to improving environmental quality [6].

Gvozdenac-Urošević [34] proposed that EE could be considered a tool for attaining sustainable economic development. However, EE is a conceptually problematic term because there is no single accepted explanation. The researcher analyzed EE and GDP for 128 countries in 2007, with mixed results. This study supports the idea that EE affects innovation development. The existing literature on EE only emphasizes issues related to energy security and energy consumption reduction [34], [35].

The greener energy programs must be funded by government expenditure for proper R&D initiatives that will lead to economic development and enhance environmental conditions [8]. More recently, Liu et al. [22] investigated the nexus of RE electricity and EC. The findings show that electricity generation from renewable sources is necessary to achieve zero emission targets. At the same time, the increase in EC, imports, GDP, and carbon neutrality targets is challenging to achieve.

More recently, Miremadi et al. [35] identified the effect of research, development, and knowledge on technological innovation [35]. The researchers suggest that the federal government's support for R&D activities increases the proportion of technological innovation. For instance, Napp et al. [36] stressed the importance of advanced technologies and R&D efforts to achieve low-carbon economies. Abolhosseini et al. [37] suggest that RE supply and consumption have become imperative because of global climate change. Green energy technologies can play a significant role in reducing pollution emissions. The use of green technologies helps to address environmental issues. They are helpful for economic growth and technological innovation through the public's expenses on technological progression, which is the foremost driver of climate change and emission reduction factors [19], [37]. Similarly, innovative and efficient technologies are economically feasible, and their annual R&D funding provides better investment incentives with low-cost budgets and escalates cleaner and greener production [38].

C. RE, Socioeconomic Development, and Structural Change

In the case of Pakistan, Wesseh and Lin [39] proposed that there is a positive association between RE and socioeconomic improvement. The findings argued that SECs induce the use of greener energy. Shahbaz et al. [40] examined the significant impact of RE on economic development. This study demonstrated that an increase in RE electricity substantially improves a country's socioeconomic development. In another study, researchers estimated the GDP for 116 economies with consistent results. An increase in RE helps enhance GDP through capital information. Rafique et al. [44] observed the impacts of EC on

RE demand [43], [44]. They use panel data from the E7 and G7 economies. The conclusions indicate that EC, as a structural change indicator, is essential for cleaner, greener energy, and pollution mitigation. Khan et al. [45] conducted a comprehensive bibliometric study on electronic government and corruption. The results suggest that electronic governments alone may not be a solution for resolving the corruption.

Furthermore, there is an association between EC and RE, enabling a country to achieve its economic development goals. Many researchers and their studies have examined this relationship, and their conclusions are consistent with the available literature. Rafique et al. [44] found a positive correlation between green energy and EC. Higher EC is associated with rising economic structural transformation. The empirical results show that EC significantly affects greenhouse gas (GHG) emissions, which should be considered in climate policymaking. Struckell et al. [46] examine the ecological determinants of innovative home ecosystems by focusing on emerging smart homes. The results suggest that single company and industry should invest resources in intelligent homes and find sustainable solutions [46]. More recently, Chauhan et al. [47] argued that collaborative innovation, collaborative processes, and technologies are vital factors for product development and achieving sustainable development goals.

Similarly, Talwar et al. [48] reported that digitalization and technological advancements are significant factors for sustainability, environmental protection, and tourism growth.

The above-discussed review of extant literature guides us to a considerable gap in the literature regarding the role of R&D budgets, technological innovations, SECs, and greener energy. Only a few studies have analyzed the role of R&D budgets and SECs. Against this backdrop, the current study attempts to provide novel conclusions and implications for Australia.

III. DATA SPECIFICATION AND METHODOLOGY

A. Data and Model Specification

This study uses time-series data (quarterly data) for Australia, covering the period from 1994Q1 to 2019Q4. The only dependent variable used here is greener energy generation in the MWH (REC) based on the objectives of the study. However, the RDBRE, RDBEF, and RDBCST were used in this study. In addition, the remaining four variables are considered as controlled variables, including patents by residents (PTR) that capture technological innovation, GDP, economic growth, SECs, and EC. The variables and their specifications are provided in Table I.

1) *Model Specification*: Since the current study used three independent and controlled variables, it constructed three models that separately compute independent and controlled variables. Notably, R&D budgets represent the fiscal variable in dollars, which shows the impact of the overall financing of RE, EE, and technologies on greener energy. EC shows structural changes and diversification effects on greener energies.

The current study followed those of Corazza and Saluto [13], Fujiwara [18], and Rafique et al. [44]. These studies provide theoretical linkages between the role of R&D investments and budgets for sustainable development and production, and the role of structural change in greener energy growth. From a logical point of view, the reduction in R&D causes a lag in technological advancement, which has adverse effects on climate change mitigation. The R&D budgets are essential policy tool for attaining

TABLE I
DATA SPECIFICATION

Variable	Specification	Unit	Data source
<i>REC</i>	Renewable energy	Generation of renewable energy in MWH	BP statistics, (2022)
<i>RDBRE</i>	R&D budget for renewable energy	Constant 2010 US\$	International Renewable Energy Agency, (2022)
<i>RDBEF</i>	R&D budget for EE	Constant 2010 US\$	International Renewable Energy Agency, (2022)
<i>RDBCST</i>	R&D budget for science and technologies	Constant 2010 US\$	International Renewable Energy Agency, (2022)
<i>GDP</i>	Economic growth	Constant 2010 US\$	World Bank, (2022)
<i>PTR</i>	Patents by residents	Index data	World Bank, (2022)
<i>SEC</i>	Socioeconomic conditions, including unemployment, poverty, and consumer confidence	Index	ICRG, (2022)
<i>ECI</i>	Complexity as product diversification and structural change	Index	Observatory of EC (2022)

energy independence, bringing enormous economic, social, and environmental benefits. From a variable selection point of view, all variables represent different factors, such as budget, structural change, and social change. The generally constructed models are as follows.

a) *Model 1:*

$$REC_t = f(RDBRE_t, PTR_t, GDP_t, SEC_t, ECI_t).$$

Model 1 indicates that RDBRE, PTR, GDP, SEC, and ECI are combined functions of REC.

b) *Model 2:*

$$REC_t = f(RDBEF_t, PTR_t, GDP_t, SEC_t, ECI_t).$$

Model 2 indicates that RDBEF, PTR, GDP, SEC, and ECI are combined functions of REC.

c) *Model 3:*

$$REC_t = f(RDBCST_t, PTR_t, GDP_t, SEC_t, ECI_t).$$

Model 3 indicates that RDBCST, PTR, GDP, SEC, and ECI are the combined functions of the REC. However, these models can be transformed into regression models according to the requirements of an econometric investigation, as follows:

$$REC_t = \alpha_1 + \alpha_2 RDBRE_t + \alpha_3 PTR_t + \alpha_4 GDP_t + \alpha_5 SEC_t + \alpha_6 ECI_t + \varepsilon_t \quad (1)$$

$$REC_t = \beta_1 + \beta_2 RDBEF_t + \beta_3 PTR_t + \beta_4 GDP_t + \beta_5 SEC_t + \beta_6 ECI_t + \varepsilon_t \quad (2)$$

$$REC_t = \gamma_1 + \gamma_2 RDBCST_t + \gamma_3 PTR_t + \gamma_4 GDP_t + \gamma_5 SEC_t + \gamma_6 ECI_t + \varepsilon_t \quad (3)$$

where REC indicates the dependent variable—representing RE generation; on the other hand, RDBRE denotes the R&D budget for RE, REBEF indicates the R&D budget for EE, and RDBCST is the R&D budget for science and technology. PTR, GDP, SEC, and ECI are the control variables discussed above. In addition, the α 's, β 's, and γ 's are the predicted coefficients and ε 's is the error term for each regression model.

B. Estimation Strategy

The present study applies various time-series econometric instruments, including descriptive statistics and normality tests of each variable under consideration. Additionally, unit root tests for stationarity with breaks have also been employed to identify the presence of unit roots and unveil the possible structural breaks in each time series. Once the unit root test results are obtained, this will allow efficient estimator(s), whether limited to the long run or both the short and long run, based on the directions from the unit root test findings. Once the results are obtained, this study also utilizes a series of diagnostic tests, which are detailed as follows.

1) *Preliminary Analysis:* Before empirically investigating the influence of each exogenous variable on RE. This study provides descriptive statistics for each study variable. Descriptive statistics are important as they summarize the entire dataset. Specifically, the descriptive statistics used here include the mean value, median, and standard deviation, which are the deviations of the observation from the mean value. Additionally, the descriptive statistics provide the range values, identifying each variable's minimum possible and maximum existing values. Along the same lines, descriptive statistics also provide skewness and kurtosis values for each variable, which are essential in analyzing the normality of the time series. However, an efficient estimator, known as the Jarque–Bera normality test proposed by Jarque and Bera, is employed to investigate the time series extensively [49].

This test considers skewness and excess kurtosis to indicate whether a time series is normally distributed. In addition, the test assumes the skewness and excess kurtosis to be equal to the zero–null hypothesis. In contrast, this hypothesis will be rejected if the Jarque–Bera normality test statistics are significant at the 1%, 5%, or 10% levels. Moreover, the Jargue–Bera computation is based on the following equation:

$$JB = \frac{N}{6} \left(S^2 + \frac{(K-3)^2}{4} \right) \quad (4)$$

where (4) illustrates that JB is the Jargue–Bera statistic(s), N is the number of observations, S is the skewness, and $K-3$ is the excess kurtosis.

To analyze whether the data time series under consideration hold unit root, this study tested for the stationarity of each variable. If the time variables consist of a unit root, it is compulsory to analyze and make them stationary regardless of leveled [I(0)] data or the first differenced [I(1)] data.

A unit root test is used to discover nonstationary time-series variables with a unit root. However, ignoring such a unit root presence may lead to inconsistent and inefficient estimates, that is, spurious regression—a high R^2 value and significant coefficients [50]. In this regard, this study employs the ZA unit root test proposed by Zivot and Andrews [51]. Hence, structural break(s) are identified in the time-series data, which might lead to estimation biases. This test can detect structural breaks and calculate unit root attributes at various levels. Moreover, this test evaluates the unit root test for a time variable by allowing for only one structural break in the time series, which may appear in the intercept, trend, or both.

These three strands can be computed as follows:

$$\Delta z_t = \varphi_1 + \varphi_2 t + \theta z_{t-1} + \emptyset DU_t \sum_{i=0}^r \omega_i \Delta z_{t-1} + \varepsilon_t \quad (5)$$

$$\Delta z_t = \varphi_1 + \varphi_2 t + \theta z_{t-1} + \pi DT_t + \sum_{i=0}^r \omega_i \Delta z_{t-1} + \varepsilon_t \quad (6)$$

$$\Delta z_t = \varphi_1 + \varphi_2 t + \theta z_{t-1} + \emptyset DU_t + \pi DT_t + \sum_{i=0}^r \omega_i \Delta z_{t-1} + \varepsilon_t \quad (7)$$

where (1) suggests a break in the intercept, (2) suggests a break in the trend, and (3) suggests a break in both the intercept and trend. Here, Tb is the possible breakpoint and r is the lag length with an upper limit in the explanatory variable(s). In addition, $DU_t = 1$ and DT_t correspond to $t - Tb$ when t is more significant than Tb , whereas it will be zero if the opposite is true.

a) *Parameter selection using LASSO algorithm:* Greener energy is associated with several factors, including budgets, income level, socioeconomic status, human knowledge, skills and technological innovation, habits, and energy prices. It is important to mention here that not all the factors carry the same importance and selecting the right set of controls is best achieved when most of the context-specific pieces of information are accounted for. In this context, the machine learning method of least absolute shrinkage and selection operator (LASSO) helps us to efficiently choose the feature selection. The LASSO selection technique relies on the assumption of approximate sparsity of models, indicating the higher number of independent variables of the model and the factors relevant to capture main features of regression. In recent studies, this method has been employed for feature selection in predicting solar power energy and income-mediated energy in Viet Nam among others [52], [53]. The LASSO algorithm is a regularization method that reduces the variance arising from the standard ordinary least squares approach or ARDL method by introducing some bias in the coefficients. In doing so, the model reduces the residual sum of squares (ZSS) and a penalty consisting of a tuning parameter lambda and the sum of coefficients β_i values

$$\min \left(\text{ZSS} + \lambda \sum \beta_i \right). \quad (8)$$

The machine learning methods are often criticized on the weak theoretical background. Against this backdrop, Chernozhukov et al. [63] developed an improvement in the LASSO algorithm, which relies on the theoretically grounded data-driven choice of penalty-level lambda, known as rigorous LASSO.¹

2) *ARDL Bounds Testing:* Unit root tests provide a mixed order of integration for the variables under consideration. This allows this study to utilize an efficient estimator considering a mixed integration order. Specifically, the study required an efficient estimation approach to determine the variables' long- and short-run associations. To explore the long-term relationships, the current study utilized the ARDL bound testing approach proposed by Pesaran and Shin [55] and a further extension was provided by Pesaran et al. [56]. For both long- and short-run analyses, the ARDL bound testing technique to cointegration approximation delivers an unbiased and efficient result [57]. With a smaller sample size of variables, this estimator tackled the issues of missing variables and autocorrelation. In addition, the ARDL bounds test technique may differentiate between dependent and explanatory variables and examine the link between mixed-order integration, that is, $I(0)$ and $I(1)$, in the

variables [58], [59]. The ARDL bounds testing formulation of the chosen variables can be expressed in the following equations for the three models of (1), (2), and (3) that can be transformed into (9), (10), and (11):

$$\begin{aligned} \Delta \text{REC} = & c_1 + \sum_{i=1}^p \alpha_1 \Delta \text{RDBRE}_{t-r} + \sum_{i=0}^q \alpha_2 \Delta \text{PTR}_{t-r} \\ & + \sum_{i=0}^r \alpha_3 \Delta \text{GDP}_{t-r} + \sum_{i=0}^s \alpha_4 \Delta \text{SEC}_{t-r} \\ & + \sum_{i=0}^t \alpha_5 \Delta \text{ECI}_{t-r} + \lambda_1 \text{RDBRE}_{t-1} + \lambda_2 \text{PTR}_{t-1} \\ & + \lambda_3 \text{GDP}_{t-1} + \lambda_4 \text{SEC}_{t-1} + \lambda_5 \text{ECI}_{t-1} + \varepsilon_t \quad (9) \end{aligned}$$

$$\begin{aligned} \Delta \text{REC} = & c_1 + \sum_{i=1}^p \beta_1 \Delta \text{RDBEF}_{t-r} + \sum_{i=0}^q \beta_2 \Delta \text{PTR}_{t-r} \\ & + \sum_{i=0}^r \beta_3 \Delta \text{GDP}_{t-r} + \sum_{i=0}^s \beta_4 \Delta \text{SEC}_{t-r} \\ & + \sum_{i=0}^t \beta_5 \Delta \text{ECI}_{t-r} + \lambda_1 \text{RDBEF}_{t-1} + \lambda_2 \text{PTR}_{t-1} \\ & + \lambda_3 \text{GDP}_{t-1} + \lambda_4 \text{SEC}_{t-1} + \lambda_5 \text{ECI}_{t-1} + \varepsilon_t \quad (10) \end{aligned}$$

$$\begin{aligned} \Delta \text{REC} = & c_1 + \sum_{i=1}^p \gamma_1 \Delta \text{RDBCST}_{t-r} + \sum_{i=0}^q \gamma_2 \Delta \text{PTR}_{t-r} \\ & + \sum_{i=0}^r \gamma_3 \Delta \text{GDP}_{t-r} + \sum_{i=0}^s \gamma_4 \Delta \text{SEC}_{t-r} \\ & + \sum_{i=0}^t \gamma_5 \Delta \text{ECI}_{t-r} + \lambda_1 \text{RDBCST}_{t-1} + \lambda_2 \text{PTR}_{t-1} \\ & + \lambda_3 \text{GDP}_{t-1} + \lambda_4 \text{SEC}_{t-1} + \lambda_5 \text{ECI}_{t-1} + \varepsilon_t. \quad (11) \end{aligned}$$

The validation of cointegration allows for the analysis of long-run coefficients, which can be presented as follows: from the equations mentioned above, Δ operates the first difference; p , q , r , s , and t indicate the lag length; and the α 's, β 's, and γ 's are the coefficients to estimate for Models 1, 2, and 3, respectively. Additionally, the long-run association can be expressed through two hypotheses: First, the null hypothesis demonstrates the absence of cointegration, which may be described as ($H_0 : \lambda_1 = \lambda_2 = \lambda_3 = \lambda_4 = \lambda_5 = 0$). Second, the alternative hypothesis indicates the presence of cointegration between the study variables and may be described as follows ($H_1 : \lambda_1 \neq \lambda_2 \neq \lambda_3 \neq \lambda_4 \neq \lambda_5 \neq 0$):

$$\begin{aligned} \Delta \text{REC}_t = & c_1 + \sum_{k=1}^p \alpha_1 \Delta \text{RDBRE}_{t-k} + \sum_{k=0}^q \alpha_2 \Delta \text{PTR}_{t-k} \\ & + \sum_{k=0}^r \alpha_3 \Delta \text{GDP}_{t-k} + \sum_{k=0}^s \alpha_4 \Delta \text{SEC}_{t-k} \\ & + \sum_{k=0}^t \alpha_5 \Delta \text{ECI}_{t-k} + \mu_t \quad (12) \end{aligned}$$

¹This LASSO algorithm is implemented in the "hdm" package of R.

$$\begin{aligned}\Delta \text{REC}_t = & c_1 + \sum_{k=1}^p \beta_1 \Delta \text{RDBEF}_{t-k} + \sum_{k=0}^q \beta_2 \Delta \text{PTR}_{t-k} \\ & + \sum_{k=0}^r \beta_3 \Delta \text{GDP}_{t-k} + \sum_{k=0}^s \beta_4 \Delta \text{SEC}_{t-k} \\ & + \sum_{k=0}^t \beta_5 \Delta \text{ECI}_{t-k} + \mu_t\end{aligned}\quad (13)$$

$$\begin{aligned}\Delta \text{REC}_t = & c_1 + \sum_{k=1}^p \gamma_1 \Delta \text{RDBCST}_{t-k} + \sum_{k=0}^q \gamma_2 \Delta \text{PTR}_{t-k} \\ & + \sum_{k=0}^r \gamma_3 \Delta \text{GDP}_{t-k} + \sum_{k=0}^s \gamma_4 \Delta \text{SEC}_{t-k} \\ & + \sum_{k=0}^t \gamma_5 \Delta \text{ECI}_{t-k} + \mu_t.\end{aligned}\quad (14)$$

From the equations mentioned above, Δ operates as the first difference, the $\alpha's$, $\beta's$, and $\gamma's$ are the long-run coefficients to estimate. In addition, c_1 is a constant term, while μ_t is the noise error term and denotes the structural break. Moreover, the short-run dynamic for the variables under discussion can be derived via the following error correction model:

$$\begin{aligned}\Delta \text{REC}_t = & c_1 + \sum_{k=1}^p \alpha_1 \Delta \text{RDBRE}_{t-k} + \sum_{k=0}^q \alpha_2 \Delta \text{PTR}_{t-k} \\ & + \sum_{k=0}^r \alpha_3 \Delta \text{GDP}_{t-k} + \sum_{k=0}^s \alpha_4 \Delta \text{SEC}_{t-k} \\ & + \sum_{k=0}^t \alpha_5 \Delta \text{ECI}_{t-k} + \kappa \text{ECT}_{t-1} + \mu_t\end{aligned}\quad (15)$$

$$\begin{aligned}\Delta \text{REC}_t = & c_1 + \sum_{k=1}^p \beta_1 \Delta \text{RDBEF}_{t-k} + \sum_{k=0}^q \beta_2 \Delta \text{PTR}_{t-k} \\ & + \sum_{k=0}^r \beta_3 \Delta \text{GDP}_{t-k} + \sum_{k=0}^s \beta_4 \Delta \text{SEC}_{t-k} \\ & + \sum_{k=0}^t \beta_5 \Delta \text{ECI}_{t-k} + \kappa \text{ECT}_{t-1} + \mu_t\end{aligned}\quad (16)$$

$$\begin{aligned}\Delta \text{REC}_t = & c_1 + \sum_{k=1}^p \gamma_1 \Delta \text{RDBCST}_{t-k} + \sum_{k=0}^q \gamma_2 \Delta \text{PTR}_{t-k} \\ & + \sum_{k=0}^r \gamma_3 \Delta \text{GDP}_{t-k} + \sum_{k=0}^s \gamma_4 \Delta \text{SEC}_{t-k} \\ & + \sum_{k=0}^t \gamma_5 \Delta \text{ECI}_{t-k} + \kappa \text{ECT}_{t-1} + \mu_t.\end{aligned}\quad (17)$$

From (13), (14), and (15), ECT_{t-1} indicates the error correction term representing the speed of adjustment toward the long-run equilibrium if any shock occurs. Moreover, to gain at the long-run equilibrium point, the ECT_{t-1} value must be negative and statistically significant [52]. Furthermore, diagnostic

TABLE II
DESCRIPTIVE STATISTICS

	ECI	LGDP	LPTR	LRDBCST T	LRDBE F	LRDB RE	LNRE C	SEC
Mean	0.2692	27.6608	7.7537	16.3823	16.9681	17.373 5	4.2460	8.9536
Median	0.3086	27.6871	7.8048	16.6502	16.8699	17.402 3	4.0517	9.1900
Maximum	0.5055	28.0029	8.0265	18.7244	18.4634	19.800 0	5.0296	10.2900
Minimum	-0.1178	27.2191	7.4730	12.0436	15.8362	15.750 4	3.8240	6.2500
Std. Dev.	0.1680	0.2323	0.1607	1.5043	0.6356	1.0067	0.4004	0.9659
Skewness	-0.7089	-0.2466	-0.5670	-0.3571	0.4772	0.4791	0.5556	-1.4494
Kurtosis	2.9065	1.8820	1.9202	2.3992	2.4424	2.3921	1.7719	4.3930
Jarque-Bera	8.7504	6.4704	10.6262	3.7746	5.2956	5.5803	11.886 4	44.8222
Probability	0.0125	0.0393	0.0049	0.1514	0.0708	0.0614	0.0026	0.0000
Observations	104	104	104	104	104	104	104	104

tests, such as the Durbin–Watson serial correlation test, were proposed by Durbin and Watson [53]. This test quantifies the serial correlation between the adjacent least squares residuals and has good size and power compared with the other existing methods [60], [61].

Dynamic autoregressive distributed lag (Dyn-ARDL) simulations using time-series data are gaining rapid recognition in energy and environmental economics [62]. The novel dynamic ARDL simulation technique effectively assesses cointegration and long- and short-run equilibrium interactions at both levels and differences. The novel dynamic ARDL simulations offer a graphical interface that explores possible hypothetical changes in the chosen variable using the ceteris paribus concept [51]. We added plot estimates with confidence intervals to the dynamic simulated ARDL.

IV. EMPIRICAL ANALYSIS AND RESULTS

In this section, the outcomes and discussion are provided. The following estimation stepwise procedure describes the descriptive statistics; the ZA unit root tests, the machine learning technique of LASSO, and dynamic ARDL tests are applied. This section also presents a graphical representation of LASSO and dynamic ARDL findings.

A. Descriptive Statistics

The average values of EC, GDP, PTR, R&D budgets for technologies (RDBCST), RDBEF, RDBRE, renewable energy use (REC), and SEC are shown with their median, maximum, and minimum values in Table II. The median values of these variables are almost identical to their average values, indicating the balancing point of the data. Standard deviations indicate the volatility of the variables. This shows how the data are spread from the average values of the corresponding variables. Skewness values range between +2 and -2 and +7 and -7 for kurtosis, which depicts the normal distribution of the research variables. Likewise, the Jarque–Bera test confirmed the expected data distribution. Comprehensive statistics indicate that information is proportioned and symmetrical.

TABLE III
ZA UNIT ROOT TEST WITH STRUCTURAL BREAKS

ZA Unit Root Test				
Variable	I(0)	Structural break	I(1)	Structural break
<i>REC</i>	-2.950	2003Q3	-6.070***	2010Q3
<i>RDBRE</i>	-4.203*	2014Q1	—	—
<i>RDBEF</i>	-4.109	2011Q2	-6.984***	2003Q3
<i>RDBCST</i>	-3.011	2004Q2	-8.731***	2014Q1
<i>PTR</i>	-3.974	2005Q2	-6.937***	2014Q1
<i>GDP</i>	-1.766	2015Q4	-4.223*	2016Q1
<i>SEC</i>	-4.844**	1999Q4	—	—
<i>ECI</i>	-4.318*	2014Q2	—	—

Significance level is denoted by ***, **, and * for 1%, 5%, and 10%. Here, the critical value for 1% is -4.93, for 5% is -4.42, and for 10% is -4.11.

TABLE IV
FEATURES SELECTION BY LASSO TECHNIQUE

rLasso Coefficients	REC Estimate
<i>Intercept</i>	-38.346
<i>LRDBRE</i>	-3.8176
<i>LRDBEF</i>	-3.4861
<i>LRDBCST</i>	0.8732
<i>LPTR</i>	1.4079
<i>LGDP</i>	-6.5344
<i>SEC</i>	0.8619
<i>ECI</i>	-0.400384
<i>Residual standard error</i>	0.075
<i>Multiple R-squared</i>	0.964
<i>Adjusted R-squared</i>	0.9629
<i>Joint Significant test</i>	4.792***

Statistical significance: * $p < 0.05$; ** $p < 0.01$; *** $p < 0.001$.

B. Analytical Techniques of Unit Root and LASSO Algorithm

ZA structural break unit root test was employed to analyze the order of integration in the data [51]. Before examining the relationship between the variables, the ZA unit root test is presented in Table III. Several unit root tests have emerged according to the number of structural breaks. For a unitary structural break, the ZA unit root test is best fitted, and it is applied to check the integration order of the variables. This is because of the increasing efficiency of identifying structural breaks and any integration of variables. The outcomes show that the test rejects the null hypothesis, portraying a structural break in the variables. The test explains that few variables show two structural breaks at the first difference.

The unit root tests show that the structural breaks for renewable energy occurred in Q3 of 2003, 2008, and 2010. The RDBRE had structural breaks in Q1 and Q3 of 2014 and Q2 of 2005 and 2010, respectively. In contrast, the SEC had structural breakpoints in Q4 and Q3 of 1999, and Q2 of 2000 and 2012. While RDBEF has breakpoints in Q2 of 2011 and Q3 of 2003 and breaks in 2004Q2–2014Q2 at I(0) and 2002Q4–2008Q4 at I(1), R&D for technology has structural breaks in Q2 of 2004, Q1 of 2014, 2002Q3–2009Q2, and 2008Q3–2013Q3. These commonly occur due to financial or economic crises that can be considered shocks in the data. In accordance with these unit root test results, the yearly quarters are the main breakpoints throughout the data. These breaks represent unpredicted changes in the data. Owing to structural breaks in the data, the unit root test null hypothesis is verified and shown in both the test results of the research variables.

Table IV presents the variables as per the LASSO test. Only the variables contributing the most to each outcome's variance are reported. The models selected respectively 7 out of 13 explanatory variables.² The empirical models are found to have joint significance of the coefficients and the null hypothesis is

rejected in all three cases [58]. The *R*-squared adjusted values reach 0.95 and 0.96 for each outcome, respectively. The next step is the autoregressive approach to determine the relationships of variables in the three models.

C. ARDL Empirics

After examining the stationarity criteria, we proceed toward the cointegration analysis. The ARDL cointegration is an extensively used econometric technique for examining long-run relationships. It is known as the bound technique, as it utilizes different orders of integration, unlike other time-series econometric approaches. The cointegration approach of ARDL is employed when the order of integration is I(0), I(1), or both. The null hypothesis of the bound test is that there is no integration with the alternative hypothesis. It is robust when determining the single long-run association of the study's fundamental variables.

The first model has RDBRE, the second model comprises RDBEF, and the third model has R&D budgets for technologies (RDBCST). Supplementary variables are utilized in all three models along with PTR, GDP, SEC, and ECI. The short-run results of ARDL show that PTR and EC have significant effects on Models 1 and 2. GDP had a significant relationship with RDBEF and RDBCST in Models 2 and 3, respectively. This supports the claim that GDP and R&D on technologies positively impact RE, which helps environmental sustainability [22]. More specifically, the results argue that RDBEF and science and technology purpose affect the greener energy generation. Such finding justifies that budgets for EE and technological advancements goals are appropriately used for greener energy adoption and greener energy generation sources. In comparison, SECs had no effect in the short-run ARDL analysis. The long-run outcomes of the autoregressive distributive technique are presented in Table V.

Greener energy generation has a significant relationship with SECs and economic growth in all three models in the long-run analysis of the study. At the same time, PTRs are significant in the R&D model for RE and EE. By contrast, EC has a significant

²Variables, which are not considered, are not reported here.

TABLE V
LINEAR ARDL RESULTS

Short-run results			
Dep. Var.	Model 1	Model 2	Model 3
<i>REC</i>			
<i>REC(-1)</i>	0.6194*** [0.1001]	0.6521*** [0.0792]	0.7267*** [0.0731]
<i>RDBRE</i>	0.0333** [0.0129]	-	-
<i>RDBEF</i>	-	0.0322** [0.0149]	-
<i>RDBCST</i>	-	-	0.0073* [0.0039]
<i>PTR</i>	0.2687*** [0.0573]	0.3281*** [0.0606]	-1.0053 [1.0584]
<i>GDP</i>	-0.5135 [0.9946]	-0.2657*** [0.9602]	0.3150*** [1.0633]
<i>SEC</i>	0.0490 [0.0873]	0.1362 [0.0860]	0.1536 [0.1453]
<i>ECI</i>	-0.2051** [0.0835]	-0.1780** [0.0810]	-0.1308 [0.0868]
<i>Cointegration Eq.</i>	-0.0745*** [0.0186]	-0.0637*** [0.0167]	-0.0874*** [0.0214]
Long-run Results			
<i>RDBRE</i>	-0.0476 [0.0681]	-	-
<i>RDBEF</i>	-	0.0593 [0.0538]	-
<i>RDBCST</i>	-	-	-0.0455 [0.0336]
<i>PTR</i>	0.5301** [0.2144]	0.4734* [0.2736]	-0.0985 [0.3892]
<i>GDP</i>	2.5585*** [0.2348]	2.3951*** [0.2648]	1.9528*** [0.3610]
<i>SEC</i>	-1.3853*** [0.2310]	-1.1916*** [0.2578]	-1.0650*** [0.2220]
<i>ECI</i>	0.0941 [0.4528]	0.3329** [0.2607]	0.1673 [0.1847]
<i>Constant</i>	-4.3537*** [1.0007]	-3.6111*** [0.9262]	-4.0184*** [1.0332]

Significance level is denoted by ***, **, and * for 1%, 5%, and 10%.
Parenthesis value shows the standard errors.

TABLE VI
DIAGNOSTIC TEST

Test		Model 1	Model 2	Model 3
R-Squared		0.7313	0.7287	0.6533
Adjusted R-squared		0.6590	0.6685	0.5709
Bound test	F-statistics	3.485**	2.948	3.085**
	t-statistics	-4.001*	-3.816*	-4.070***
E.C. test	F-statistics	3.485**	2.948	3.085*
	t-statistics	-4.001***	-3.816*	-4.070*
Durbin-Watson test		1.9426	1.9805	2.0961

Significance level is denoted by ***, **, and * for 1%, 5%, and 10%.

TABLE VII
DYNAMIC ARDL RESULTS

Dep. Var.	Model 1	Model 2	Model 3
<i>REC</i>			
<i>REC(-1)</i>	0.9424*** [0.0226]	0.9485*** [0.0201]	0.9457*** [0.0255]
<i>RDBRE</i>	-0.0075 [0.0052]	-	-
<i>RDBEF</i>	-	0.0182*** [0.0149]	-
<i>RDBCST</i>	-	-	0.0009 [0.0039]
<i>PTR</i>	0.0315 [0.0229]	0.0781*** [0.0217]	-0.0430 [0.0440]
<i>GDP</i>	0.1758*** [0.0521]	0.1955*** [0.0462]	0.1725*** [0.0549]
<i>SEC</i>	-0.0581* [0.0326]	-0.0608** [0.0860]	-0.0524 [0.0330]
<i>ECI</i>	-0.0077 [0.0311]	-0.0750*** [0.0187]	0.0269 [0.0192]
<i>Constant</i>	-4.1056*** [1.2042]	-4.7680*** [1.0734]	-4.1044*** [1.2490]
<i>R-squared</i>	0.9981	0.9985	0.9981
<i>Adjusted R-Squared</i>	0.9980	0.9984	0.9980

Parenthesis shows standard error. Significance level is denoted by ***, **, and * for 1%, 5%, and 10%.

value in Model 2, with a significance level of 5%, as shown in the following text. Furthermore, diagnostic tests of ARDL estimation were performed to check the econometric model's robustness and goodness of fit.

The bound tests are extensions of ARDL models that use t-statistics and F-statistics for the lagged values of the primary variables. They are unlike other conventional methods, which impose restrictive assumptions on the model. The t-scores of the bound and EC tests were negative. These tests imply a long-run relationship that exists between greener energy generation and R&D budgets for greener energy, EE, and technologies. Changes in R&D budgets directly affect greener energy generation. The error correction test adjusts the long-run and short-run equilibria without trailing long-run information.³

Table VI presents the findings of the diagnostic tests. The t- and F-score values of the error correction test were significant. The R-squared and adjusted R-squared values illustrate the goodness-of-fit test of the model. The higher the R-squared values and adjusted R, the better the model fits the observed data. The R-values indicate that the maximum variation in the output is explained by the input variables used. Furthermore, the values of the Durbin-Watson tests approach 2 indicate no autocorrelation problems in the empirical models. The overall diagnostic report reveals that we can further employ the dynamic ARDL method.

D. Dyn-ARDL Empirics

To extend the empirical analysis, the authors employ the dynamic ARDL introduced by Jordan and Philips [64]. The

³ Authors have reported the coefficient values, standard errors, and *p* values following the other studies. The CVs are not reported due to space constraint. The standard formula for coefficient of variation is (standard deviation/mean) × 100.

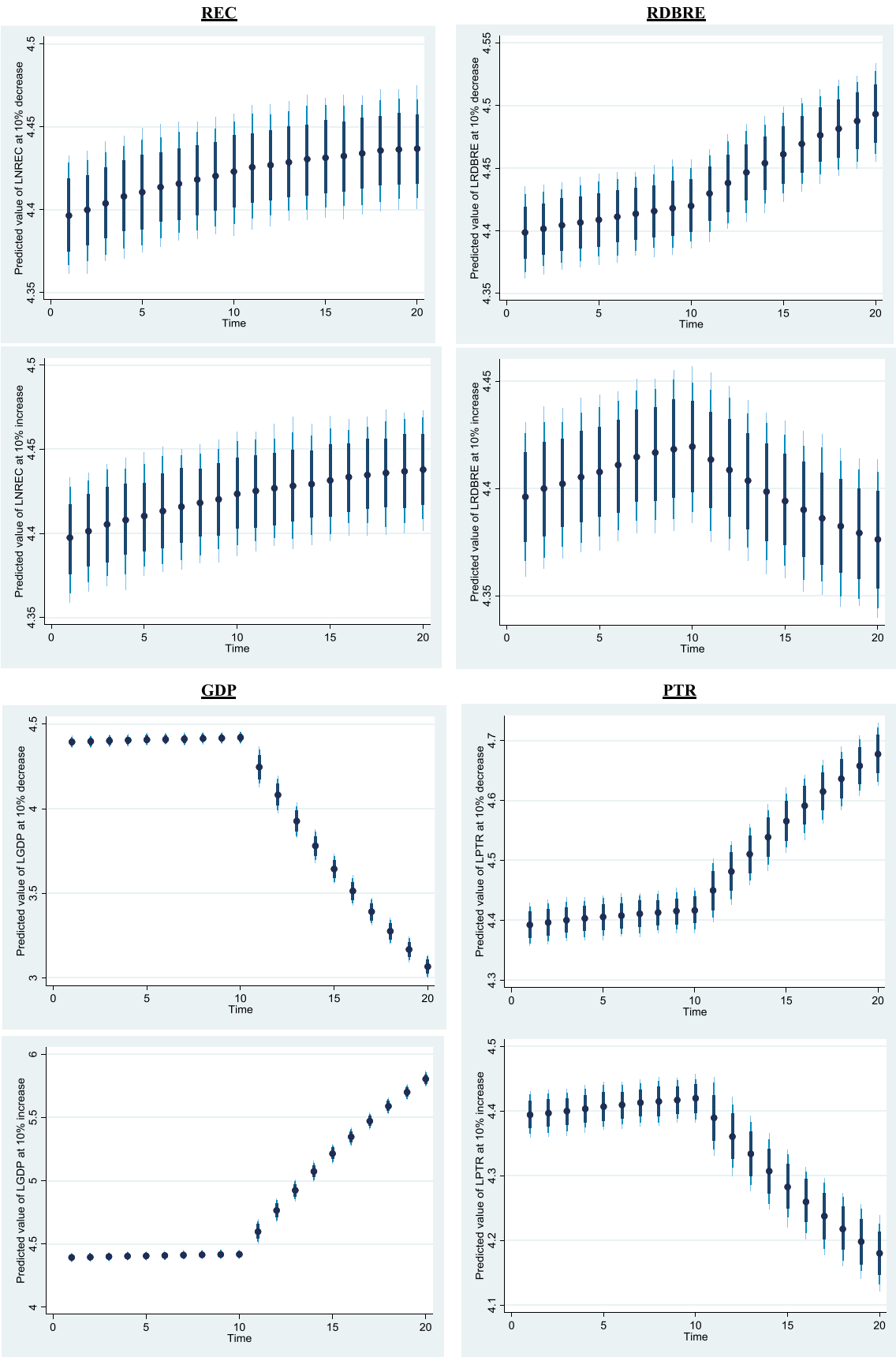


Fig. 3. Model 1 empirical estimates.

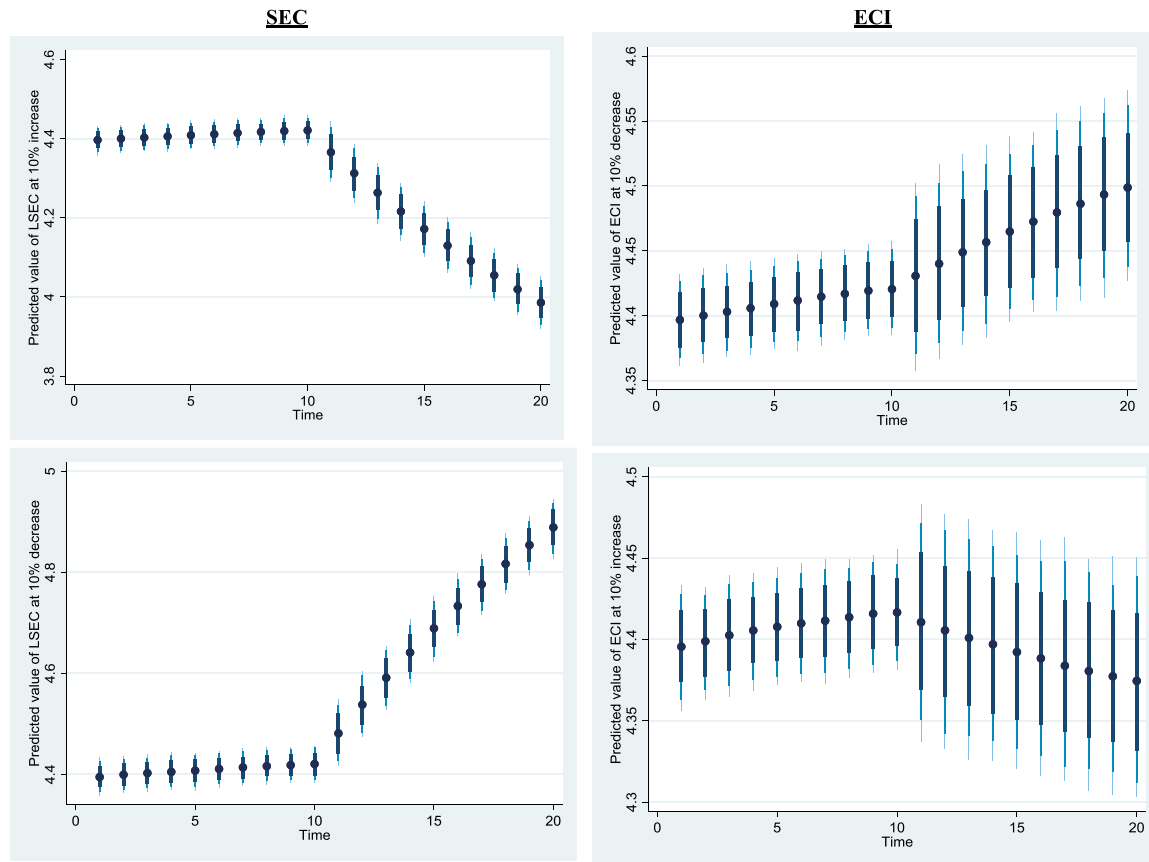


Fig. 3. (Continued.) Model 1 empirical estimates.

dynamic ARDL helps draw a single equation's counterfactual response (referred to as shock). This method provides an integrated method for determining the ARDL estimates and interpreting the effects of shocks or breakpoints. The dynamic model uses model coefficients, stationary ARDL, and cointegration relationships—these filter the changes in the dependent variables to simulate meaningful impacts in the independent variable. The dynamic ARDL results are listed in Table VII, and the graphical representations of the variables in all three models are incorporated later in the study. Figs. 3–5 present the graphical estimates for dynamic ARDL model 1, 2, and 3, respectively. Notably, in each figure (3, 4, and 5), all the variables are presented, respectively.

According to these outcomes, the R&D budgets significantly affect greener energy generation in Australia. In Model 1, SECs and GDP have significant results, with 0.10 and 0.01 levels of significance. GDP is undoubtedly (positively) related to the dependent variable, while the coefficient of SECs has a significant negative association. Greener energy generation increases with an increase in R&D for RE, GDP, and SECs. In Model 2 of R&D for EE, all the variables significantly impact RE at the 0.01 and 0.05 levels of significance. R&D for EE positively and significantly affects greener energy generation. This finding is very novel and eye catching, demonstrating the fact that R&D budgets might be the key factor for EE improvements. In addition, R&D in EE can be beneficial in enhancing economic progress because energy is considered the backbone of the country and a driving force for the global economy. Finally, the GDP is relevant and

significant for RE. Such finding shows that economic progress improves the RE generation. Technological advancements and an increasing GDP are necessary for the economy to flourish. Few of the recent studies also support this narrative [34]. The government plays an essential role in establishing budgets for technologies and has a positive association with the dependent variable. More recently, Magazzino et al. [65], [66] also reported similar conclusions apropos the role of technological advancements, economic progress, and environmental pollution.

Spike plots present a visual depiction of the breakpoints. Instead of the sizes and shapes of the spikes, timings are necessary for the analysis, as they show the structural breakpoints [67]. The responses are best visualized in the plots. The spike plots of the dependent and independent variables are shown in the dynamic ARDL graphs for Model 1, the ARDL graphs for Model 2, and the ARDL graphs for Model 3 of the study.

Overall, the results demonstrate the robustness of the empirical models. It shows that the budgets for technologies, EE, and greener energies significantly affect greener energies. The graphical spike plots show that the predicted value of the study variables in the three models decreases at a tenth and vice-versa for each variable. Additionally, the R -squared and adjusted R -squared values of the dynamic ARDL show the best goodness of fit, depicting 90% variation in the output variable, which is explained by the input variables used. Subsequently, the R -squared adjusted values confirm the robustness and efficiency of the approach. If all of these variables show a positive trend and significant association with the dependent variable, then

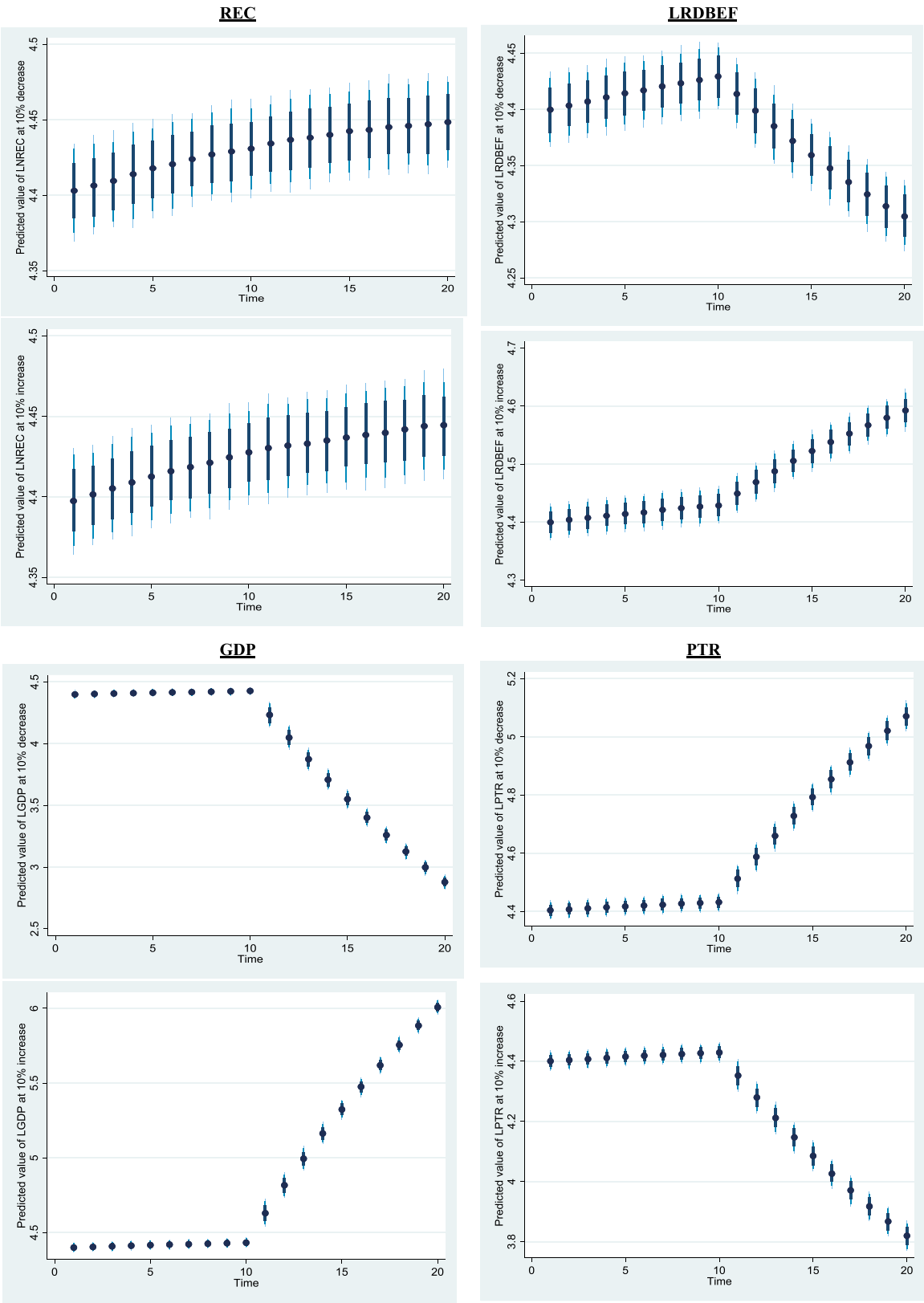


Fig. 4. Model 2 empirical estimates.

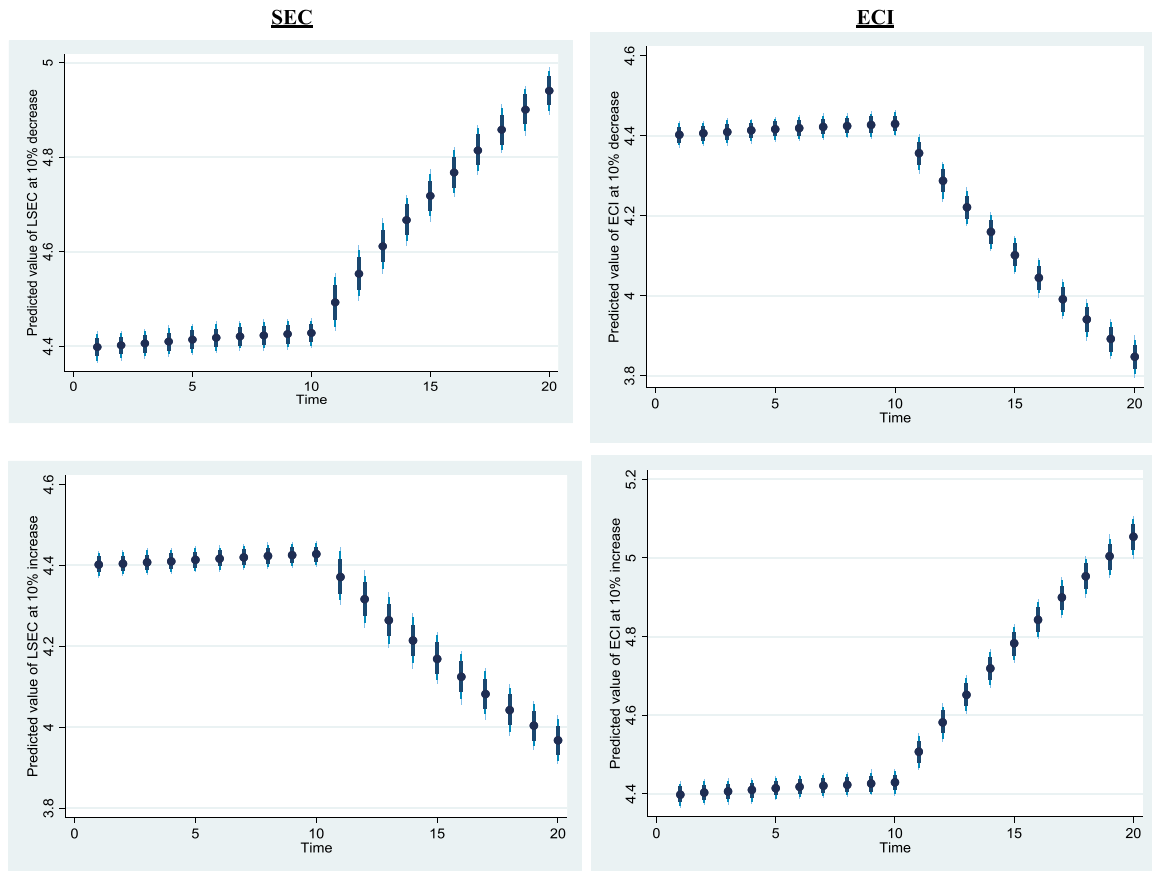


Fig. 4. (Continued.) Model 2 empirical estimates.

TABLE VIII
MULTICOLLINEARITY TEST USING VIF

Variable	VIF (Model-1)	VIF (Model-2)	VIF (Model-3)
<i>RDBRE</i>	8.85	—	—
<i>RDBEF</i>	—	1.82	—
<i>RDBCST</i>	—	—	1.02
<i>PTR</i>	3.68	4.36	3.58
<i>GDP</i>	5.52	6.62	5.26
<i>SEC</i>	2.02	2.03	1.94
<i>ECI</i>	8.81	4.04	3.04
<i>Mean VIF</i>	5.78	3.77	2.97

economic–environmental prosperity and carbon neutrality will move alongside each other. This is an asymptotically unbiased efficient estimation process. The graphical representation illustrates the cutoff points with spike plots. However, the findings showed significant outcomes at all three significance levels.

To examine multicollinearity in all the three models, this study uses the variance inflating factor (VIF) strategy. The results obtained are reported in Table VIII. From the results, it can be seen that all variables report lower VIF value than the thumb rule, i.e., 10. In this sense, the study concludes that there is no exact linear relationship between the variables under consideration, which further satisfies the key assumption of dynamic ARDL findings.

V. DISCUSSION OF FINDINGS

The diagnostic test findings for ARDL estimations revealed that the model was a good fit with the available data and indicated model sturdiness for proceeding with further analysis. The error correction test adjusted the short- and long-run information without trailing or affecting the long-run information moving toward the dynamic ARDL analysis of the study. The estimates of ARDL are flexible; however, to inculcate dynamic efficiency for structural breakpoints, a dynamic ARDL was applied. The novel dynamic approach is generally applied to capture surprises in climatic and socioeconomic situations. The presence of structural breaks in the data discussed earlier depicts changing trends in the data. These breakpoints caused fluctuations. The effect of structural breaks on the dependent variable may have varied during this period. The linear ARDL outcomes support the claim that R&D significantly influences greener energy generation. The key policy variables (R&D budgets, EC, and technological innovation) have a specific impact and significance on the greener energy generation in all three specifications. The findings for technological advancements, economic progress, and structural change are in line with the recent studies [18], [19], [42], [61], [65]. The dynamic ARDL technique pictorially depicted the presence of structural breaks, while the outcomes explicitly uncovered the relationships between the dependent and explanatory variables. The findings explain that R&D budgets in Australia are being utilized for greener energy generation and on the technologies, equipment's and resources to

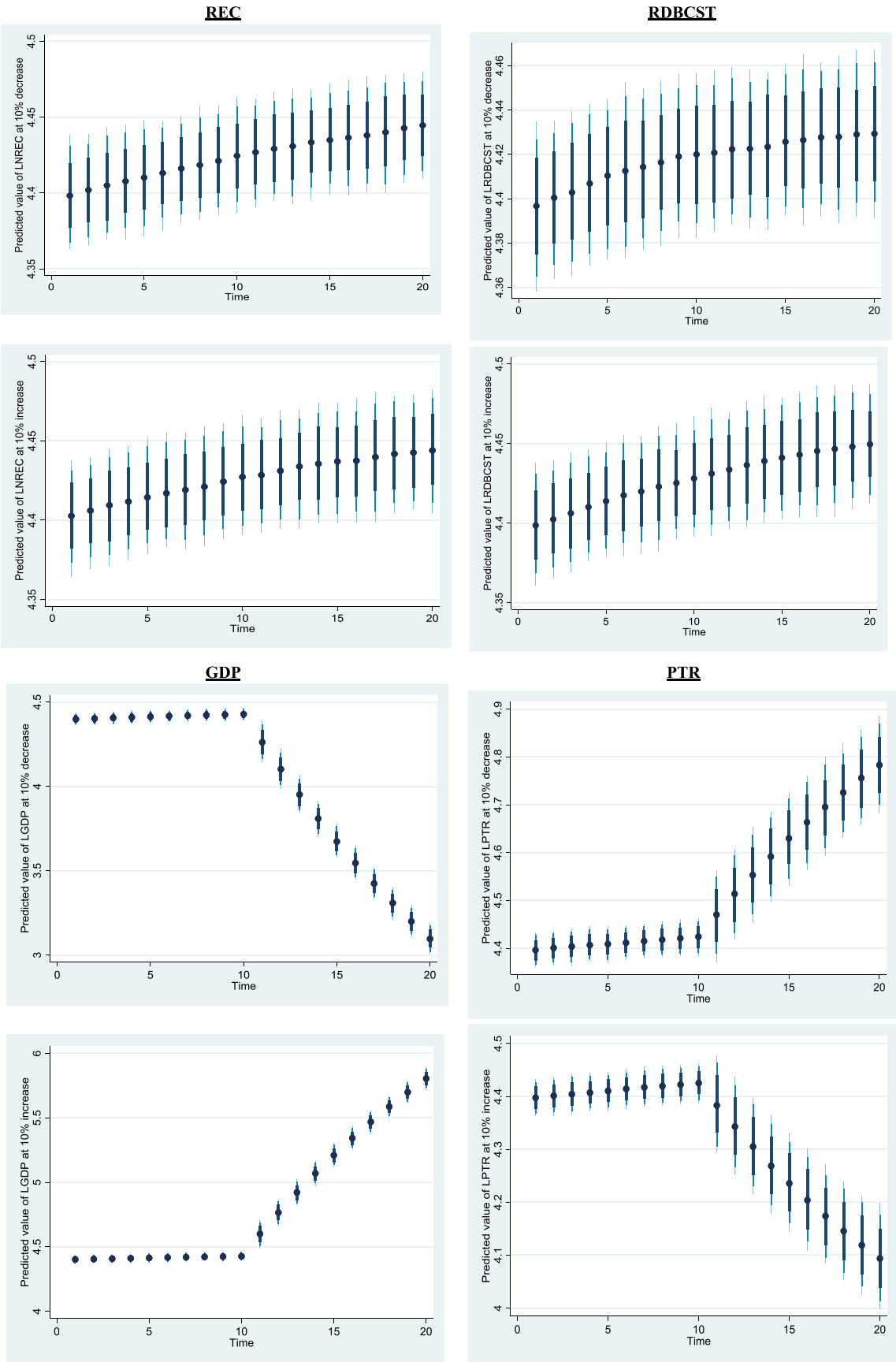


Fig. 5. Model 1 empirical estimates.

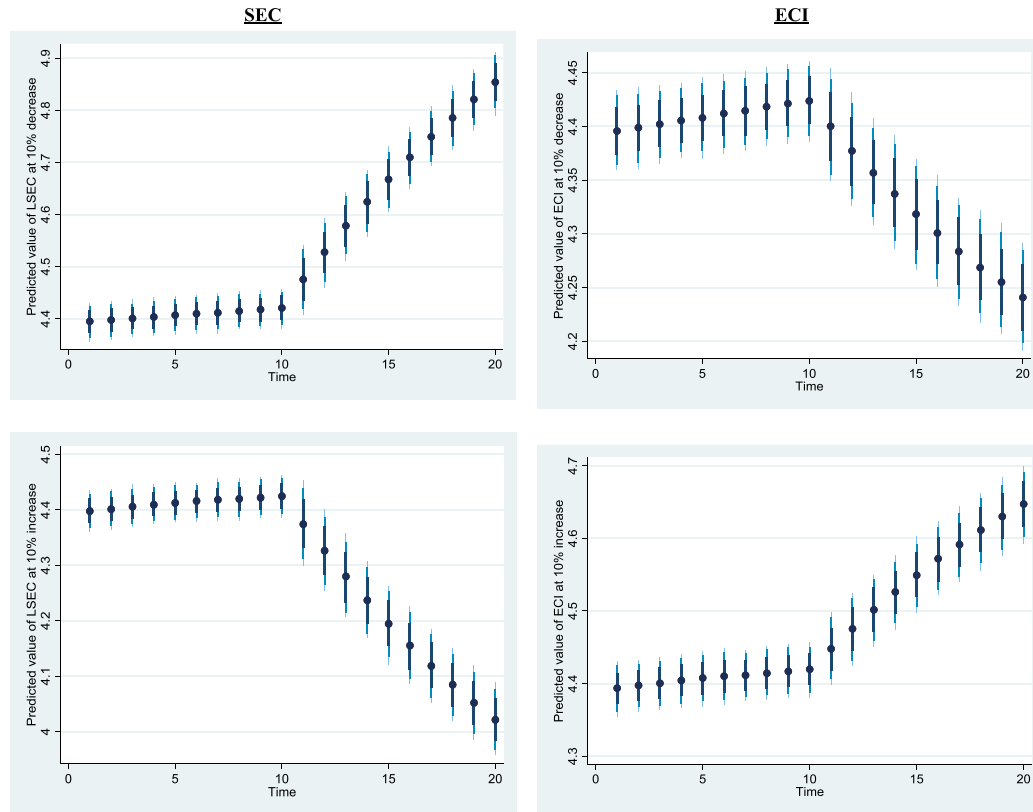


Fig. 5. (Continued.) Model 1 empirical estimates.

generate greener energy from several sources. From a policy point of view, the finding claim that R&D budgets and socioeconomic factors contribute for greener energy technology adoption. Hence, the developed countries, such as Australia, should put more emphasis on the budget allocation for research on technological advancements and discovering modern sources greener energy.

Along the same lines, the findings are consistent with recent research. For instance, Liu et al. [22] and Napp et al. [36] highlighted the importance of technologies and R&D efforts for advanced technologies in low-carbon economies, emphasizing the significant association between technological advancement and RE consumption. Hence, the present findings on R&D budgets, technological innovation, and RE generation are consistent with these works [22], [36]. Gvozdenac-Urošević [34] suggests that EE can be a tool for sustainable economic development. In the same line, Freimane and Bāliņa [19] mentioned that investment in R&D is necessary to achieve the sustainable economic progress. Increasing the budget may enhance RE generation and consumption, which benefits economic growth, technological progress, and innovation [19], [33].

Regarding the relationship between economic growth and greener energy, the findings are in line with those of the article given by Ślusarczyk et al. [26]. For the connection between EC and RE, the results depicted substantial outcomes supporting the findings of Rafique et al. [44]. Finally, for socioeconomic development and RE, this study shows significant effects, but the direction of socioeconomic development is negative in all three modifications, depicting a novel contribution to the academic and empirical literature.

Dynamic relationships exist among RE, SECs, and R&D budgets (for greener energy, EE, and technologies), which enable and assist the country in achieving economic development goals. The current study has highlighted the importance of using the R&D funds for research and green innovation objectives, which seems to be slightly missing for the case of Australia. It is a well-known fact that carbon emissions have tragic impacts on the environment and climate change. Socioeconomic expansion, technological innovation, and greener energy can help to mitigate the hazardous effects of climate change and achieve sustainable development goals. EC significantly contributes to promoting RE, as it increases network science and innovation, which is proportional to environmental sustainability [51]. Additionally, budgets for research and innovation in greener energy adoption are optimal for ecological sustainability. Increasing budgets or investing in R&D budgets using greener energy might be a useful way to mitigate the GHG emissions and improve the economic sustainability.

More specifically, the findings show interesting insights concerning R&D, EE, and RE, which allows us to draw some policy-level contribution. From a policy point of view, the R&D budgets show weak positive or insignificant effects on RE. This implies that Australia might need to focus on its greener energy generation, technologies associated with greener energy, and challenges of greener energy generation. In addition, Australian policymakers should put their effects for monitoring the R&D budgets, the budgets allocation, and the underlying challenges associated with R&D funds utilization for different objectives, such as energy transition, EE, and science and technology. In addition, Australia might need to focus on human

capital, knowledge and skills, and product diversification in manufacturing. The reason is that diversification policies might need different inputs, and RE can be considered as one potential input in this process. Technological advancements, knowledge, and skills significantly boost greener energy generation capacity due to the use of resources, budgets, and equipment's. Finally, socioeconomic changes should be considered as a key factor due to the buying behavior, confidence, and willingness to use advanced machinery and technological products, such as E-vehicles and solar-based irrigation equipment's. As a developed economy, Australia should emphasize the use of budgeted funds on technological advancements, diversification in production and on policies toward sustainable development goals, such as achieving EE low temperature, and net-zero emissions.

The goals of developed and developing economies vary regarding forecasting and measuring EE. In this regard, the environmental regulations regarding taxation and budgets are also perceived as critical factors for EE and technological advancements. For a country's socioeconomic development, measuring and forecasting EE is considered as a key factor for economic and environmental sustainability.

Overall, greener energy is vital for eliminating environmental issues and improving living standards worldwide. Unlike fossil fuels, greener energy is a long-term auxiliary and ultimate future for the world, especially regarding global climate change and carbon emission reduction. The growing concern about carbon emissions has drawn the world's attention toward RE generation. The present findings are in some way consistent with the novel outcomes of the articles presented in [19], [22], and [27] concerning all explanatory factors for RE generation [22], [26], [61]. This reveals that RDBRE, EE, and technologies can be fruitful for mitigating climate concerns and conducive to increasing RE generation for economic development and digital innovation.

VI. CONCLUDING REMARKS AND LIMITATIONS

It is central to environmental sustainability and economic development that countries increase their share of greener energy generation to replace polluting, inefficient coal, oil, and other unsafe fuel sources. The Australian economy experiences dynamic growth, along with increased income level, a reduction in poverty but on the cost of rising emissions due to coal and natural gas use. During recent decades, particular efforts have been made to expand infrastructure and reduce dependence on coal, oil, and other energy sources for industrial and manufacturing objectives. In this regard, significant R&D budgets were allocated to increase share of greener energy, EE, and technological advancements purposes. Nevertheless, the complex economic structure of Australia continues to consume huge amounts of fossil fuels (coal, oil, gas), and Australia is still lacking greener energy sources and RE generation capacity. Against this backdrop, the current study has explored the impacts of R&D budgets, socioeconomic factors, and EC of Australia on RE generation. On that account, the present study, in line with the existing research, helps clarify the link between greener energy generation and R&D funds. In this article, we employed the LASSO method, linear ARDL, and dynamic ARDL techniques for empirical analysis. The results mentioned that greener energy depends on R&D budgets, socioeconomic changes, and technological advancements.

In general, the role of R&D budgets and socioeconomic factors had been widely overlooked for greener energy generation. Therefore, this study was a novel academic contribution

to analyzing the effect of different kinds of R&D budgets in three different specifications and offered the policy-level contributions for Australia. Using green energy sources to generate electricity helped to restrict atmospheric pollution, which can be achieved through R&D in technologies. The main reason for economic development lied in the country's productivity and technological advancement. Therefore, natural resources were not being appropriately utilized in Australia, which was considered a hurdle to economic prosperity and environmental sustainability. Furthermore, financial development impacted economic growth by investing in R&D.

Based on these outcomes, it was clear that green energy use significantly enhanced environmental sustainability if effective policies were implemented. Technological and product innovation substantially impacted promoting RE generation and consumption. This required the efficient management and allocation of budgets by the government or potential investing parties. R&D of RE was imperative for any country. Countries, such as Australia, have substantially improved product innovation and R&D development projects for sustainability. However, they must transform the utilization of their natural resources toward RE use. R&D expenses and product innovation are required to increase business subdivisions.

RE boosts technological advancement and innovations for the nation's environmental sustainability and socioeconomic development. Additionally, promoting complex economic methods is fruitful for knowledge management and innovation in the economy. The country (government/non-government) should focus on this strategy because it will be beneficial both domestically and internationally in terms of sustainable innovation. Additionally, managing the inappropriate and inefficient utilization of natural resources alongside the efficient use of RE can increase the transformation toward a green economy.

The present study is limited to analyzing the impact of RDBRE generation in Australia. Future studies can extend the empirical model to panel data, including more developed economies. In addition, more control variables can be used to estimate the role of R&D budgets in greener energy and environmental quality. Future research may consider advanced economies or conduct a comparison with other developed economies for improved and vital environmental research on the policy framework. Moreover, further explanatory (control) variables can be included for future purposes, such as energy production, ethnicity, and economic innovation.

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Data Availability

Data are available upon request from the corresponding author.

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