Ekonomi, Politika & Finans Araştırmaları Dergisi, 2024, 9(3): 484-502
Journal of Research in Economics, Politics & Finance, 2024, 9(3): 484-502
Araştırma Makalesi / Research Article, https://doi.org/10.30784/epfad.1512266

FORECASTING GREEN TECHNOLOGY DIFFUSION IN OECD ECONOMIES THROUGH MACHINE LEARNING ANALYSIS

Makine Öğrenimi Analizi Yoluyla OECD Ekonomilerinde Yeşil Teknoloji Yayılımının Tahmini

Büşra AĞAN*

Abstract

An accelerating global shift towards sustainable development has made the diffusion of green technologies a critical area of focus, particularly within OECD economies. This study aims to use a machine-learning approach to explore the future diffusion of green technology across OECD countries. It provides detailed forecasts from 2023 to 2037, highlighting the varying rates of green technology diffusion (GTD) among different nations. To achieve this, the Autoregressive Integrated Moving Average (ARIMA) model is employed to offer new evidence on how the progress of green technology can be predicted. Based on empirical data, the study categorizes countries into high, moderate, and low GTD growth. The findings suggest that Japan, Germany, and the USA will experience significant growth in GTD, while countries like Australia, Canada, and Mexico will see moderate increases. Conversely, some nations, including Ireland and Iceland, face challenges with low or negative GTD values. The study concludes that applying this machine-learning model provides valuable insights and future predictions for policymakers aiming to enhance green technology adoption in their respective countries.

Keywords: Sustainable Development, Green Technology Diffusion, Environmental Sustainability, Machine Learning Analysis, ARIMA Model.

JEL Codes: O3, O33, Q55

Öz

Sürdürülebilir kalkınmaya doğru hızlanan küresel değişim, yeşil teknolojilerin yaygınlaşmasını, özellikle OECD ekonomileri içinde, kritik bir odak alanı haline getirmiştir. Bu çalışma, OECD ülkeleri genelinde yeşil teknolojinin gelecekteki yaygınlaşmasını keşfetmek için bir makine öğrenmesi yaklaşımı kullanmayı amaçlamaktadır. Farklı uluslar arasında değişen yeşil teknoloji yaygınlaşma (GTD) oranlarını vurgulayarak 2023'ten 2037'ye kadar ayrıntılı tahminler sunmaktadır. Bunu başarmak için, yeşil teknolojinin ilerlemesinin nasıl tahmin edilebileceğine dair yeni kanıtlar sunmak için Otoregresif Entegre Hareketli Ortalama (ARIMA) modeli kullanılmaktadır. Çalışma, ampirik verilere dayanarak ülkeleri yüksek, orta ve düşük GTD büyümesi olarak kategorize etmektedir. Bulgular, Japonya, Almanya ve ABD'nin GTD üzerinde önemli bir büyüme yaşayacağını, Avustralya, Kanada ve Meksika gibi ülkelerin ise orta düzeyde artışlar göreceğini göstermektedir. Tersine, İrlanda ve İzlanda dahil olmak üzere bazı uluslar, düşük veya negatif GTD değerleriyle zorluklarla karşı karşıyadır. Çalışma, bu makine öğrenmesi modelinin uygulanmasının, kendi ülkelerinde yeşil teknoloji benimsenmesini artırmayı amaçlayan politika yapıcılar için değerli içgörüler ve gelecek tahminleri sağladığı sonucuna varmıştır.

Anahtar Kelimeler: Sürdürülebilir Kalkınma, Yeşil Teknoloji Yayılımı, Çevresel Sürdürülebilirlik, Makine Öğrenimi Analizi, ARIMA Modeli.

JEL Kodları: O3, O33, Q55

* Assist. Prof. Dr., OSTİM Technical University, Department of Economics, Türkiye, busra.agan@ostimteknik.edu.tr

Received Date (Makale Geliş Tarihi): 08.07.2024 Accepted Date (Makale Kabul Tarihi): 01.09.2024

1. Introduction

Green technologies have emerged as a critical factor in transitioning towards sustainable development as the global community confronts the pressing challenges of climate change and environmental degradation. The adoption of these technologies is essential for reducing carbon emissions, improving energy efficiency, and achieving the environmental targets set by international agreements such as the Paris Agreement. Within this context, OECD economies play a pivotal role due to their economic influence and capacity for technological innovation. These technologies, which include green energy sources, energy-efficient systems, and sustainable agricultural practices, have the potential to substantially lower greenhouse gas emissions and decrease the negative impacts of climate change. The diffusion of these technologies is at least as important as their creation and development. A pioneer researcher Hall (2004) explores the concept of diffusion in innovation, describing how individuals and firms adopt new technologies or replace older ones. He supports the evidence that diffusion not only spreads innovations but also enhances them through learning, imitation, and feedback effects.

The adoption and diffusion of green technologies are essential for achieving the targets set by international agreements, such as the Paris Agreement, which aims to limit global warming to below 2 degrees Celsius above pre-industrial levels (UNFCCC, 2015). There are several studies have shown that the deployment of green energy technologies, such as wind and solar power, can substantially decrease carbon emissions while providing economic benefits and energy security (Rao and Kishore, 2010; Sun et al., 2022; Luo et al., 2024). Research by Rogers (2003) emphasizes the importance of understanding the diffusion process to facilitate the adoption of green technologies. The diffusion of innovations theory by Roger emphasizes how the characteristics of an innovation, communication channels, time, and the social system influence the adoption rate. Applying this framework to green technologies identifies barriers and accelerators in their adoption, ensuring more effective dissemination and integration into various sectors.

Another study by Dutz and Sharma, (2012) analyze that green technologies encompass a diverse array of fundamentally distinct innovations by promoting resource-efficient, clean, and resilient economic expansion. On the other hand, Dewick et al. (2006) investigate the impact of future disruptive technologies on industrial structure, economic expansion, and the environment in the 21st century. Analyzing technologies in the EU, USA, and China for 2020 and 2050, the findings indicate that while the EU and US will experience similar effects, China initially see a lesser impact, aligning with the EU and US by 2050.

Additionally, recent studies highlight the role of policy and regulatory frameworks in promoting the diffusion of green technologies. For instance, supportive policies such as subsidies, tax incentives, and renewable energy mandates have been shown to significantly boost the deployment of green energy technologies (Hao et al., 2021; Habiba et al., 2022; Sadiq et al., 2023; Zhou et al., 2023). Similarly, stringent environmental regulations can drive innovation by pushing firms to develop and adopt cleaner technologies (Meng et al., 2020; Wang et al., 2021; Luo and Mabrouk, 2022).

Despite the critical importance of GTD, traditional forecasting methods often fall short in capturing the complex and dynamic nature of technology adoption across diverse economic landscapes. In recent years, the advent of machine learning (ML) has revolutionized predictive analytics, offering advanced methodologies capable of analyzing large datasets and uncovering intricate patterns. More recently, the connections of ML and artificial intelligence in green technology forecasting further enhanced the ability to predict the diffusion of innovations. In accordance with Zhou et al. (2024) explore the impact of adopting industrial robots on regional pollution emissions in China. The findings indicate that industrial robots significantly reduce pollution emissions intensity across various provinces, confirmed by robustness tests. This analysis reveals that this reduction is due to improved energy efficiency and increased pollution reduction technologies. Moreover, Han and Yang (2024) explore financing and management strategies by using an artificial neural network (ANN) in a Chinese renewable energy company, the study finds that increasing green jobs more significantly reduces CO2 emissions than expanding renewable energy capacities.

This study focuses on applying ML approaches to forecast the diffusion of green technologies in OECD economies. The novel application of this model to green technology forecasting allows for more accurate and reliable predictions. With this purpose, the study employs a range of ML techniques, including supervised learning algorithms and ensemble methods, to model and predict the diffusion patterns of green technologies. The ARIMA model is selected for its robustness in time-series forecasting and its ability to handle the complex dynamics involved in technology diffusion. We used an extensive dataset, encompassing historical adoption rates, economic indicators, and environmental policies, to ensure the accuracy and reliability of our predictions. Therefore, forecasting of this study has divided the terms the current (1980-2022) and future (2023 and 2037) years.

The importance of this study lies in its ability to provide actionable insights for policymakers, businesses, and researchers. This study makes a significant contribution to the existing literature on technology diffusion and sustainability by integrating machine-learning techniques with economic forecasting models in several ways. First, it focuses on forecasting the future diffusion of green technology within the context of OECD countries. Second, it emphasizes the diffusion of green technology rather than its development. Third, it enhances the understanding of technological diffusion by incorporating advanced ML methods, thereby improving the predictive capabilities of existing models. Given the background, objectives, and significance of this study, the research aims to address the following key question: How will GTD progress over the next 14 years in OECD countries?

The distinctiveness of this study comes from its use of ML techniques, specifically the Autoregressive Integrated Moving Average (ARIMA) model. This method delivers novel insights into forecasting the spread of green technology in OECD countries from 2023 to 2037. The use of ARIMA allows for a detailed examination of time-series data, offering a nuanced understanding of trends and patterns that traditional methods may overlook. According to the ARIMA model's findings, most countries are showing an increasing trend in GTD, which suggests a promising future for the adoption of green technology over the forecasting period. This approach not only enhances the accuracy of forecasts but also contributes valuable evidence on the dynamics of green technology adoption and its future implications for sustainability and economic development across the OECD nations.

The study is structured as follows: Section 2 reviews the relevant literature on technology diffusion and ML in forecasting. Section 3 details the methodology, including the ARIMA model and the data used. Section 4 presents the empirical results. Section 5 concludes the study by summarizing key findings, discussing limitations, and offering policy recommendations.

2. Literature Review

The transition to green technologies is crucial for addressing climate change and promoting sustainable development. There is a growing body of theoretical and empirical studies to examine the factors that drive the development and diffusion of green technology. This body of literature is focused on the linkages between green technologies and CO2 emissions in general. Additionally, it incorporates the Environmental Kuznets Curve (EKC) framework to contextualize the relationship between economic growth and environmental degradation in the adoption of green technologies. Unlike previous literature, this literature review examines the existing body of theoretical and empirical research on GTD, highlights the determinants of this diffusion, and explores the emerging role of ML in enhancing forecasting accuracy.

The diffusion of green technologies has been extensively studied within various theoretical frameworks. Rogers' (2003) “Diffusion of Innovations” theory provides a foundational understanding of how new technologies spread within a society, emphasizing factors such as relative advantage, compatibility, complexity, trialability, and observability. This theory has been adapted to examine the adoption of green technologies, highlighting the importance of perceived benefits and barriers (Hall and Khan, 2003). Another important theoretical framework is the Technology-Organization-Environment (TOE) framework, developed by Tornatzky and Fleischer in 1990. This model considers technological, organizational, and environmental contexts as critical determinants of technological innovation adoption. In the context of green technologies, the TOE framework identifies factors such as technological readiness, organizational capabilities, and regulatory pressures that influence diffusion.

A conducted by Popp (2006) mandates energy efficiency standards and emissions reductions also drive green technologies. Addition to in the theoretical framework, Allan et al. (2013) investigate the stages of the diffusion of green technology on economic, regulatory, social, and technological factors influencing its adoption. They also identify barriers such as costs and lack of awareness and recommend financial incentives, regulatory support, public awareness campaigns, and research and development to promote the spread of environmentally friendly innovations. Later, Cohen et al. (2017) mention that the availability of financial resources and access to capital markets are critical determinants of green technology investments.

The majority of studies in the literature have concentrated on the empirical impacts and consequences of GTD. In previous studies, Lv et al. (2021) measure green innovation efficiency in 30 Chinese cities, examining the influence of financial structure, scale, and efficiency. The findings indicate that financial structure promotes green technology innovation, while financial scale and efficiency hinder it, with environmental regulation and innovation output playing moderating and mediating roles. Similarly, Xu et al. (2021) analyze the impacts of green regulation and foreign direct investment (FDI) on green innovation in 13 Chinese manufacturing sectors. The results show that ecological regulation positively impacts green innovation, while FDI negatively impacts it. Later, Maiti (2022) explores the effect of green growth on green innovation using dynamic panel threshold regression on data from 32 countries, and the findings conclude that a 1% increase in CO_2 productivity boosts green innovation, and also a 1% rise in environmental efficiency enhances green technologies.

A present study by Hussain et al. (2022b) investigates the role of environmental technology and green factors on green growth in high-GDP countries. Their empirical findings demonstrate that green technology significantly boosts environmental-friendly growth, but energy consumption and emissions decrease it. Moreover, Tuganova et al. (2022) examine the impact of green technology on sustainable development using bibliometric methods on data from Scopus and the European Patent Office. Their findings give evidence that increased research in these eco-innovation areas does not necessarily lead to more patents, highlighting skepticism about green technologies' effectiveness in solving environmental challenges. Lin and Ma (2022) investigate the effect of green technology innovations on CO_2 emissions in 264 Chinese cities, focusing on how the urban innovation environment affects this relationship. The findings reveal that green innovations significantly decrease CO_2 emissions only after 2010. On the other hand, government spending does not significantly alter the marginal effect of green technologies, underscoring the importance of human capital for effective CO_2 reduction.

Another study by Oyebanji and Kirikkaleli (2023) investigate the impact of green technology innovation, renewable electricity, financial development, and economic expansion on environmental quality in Western European countries. The results show that renewable electricity and green technologies reduce CO_2 emissions. In the context of the novel approach, Wang et al. (2023) investigate how artificial intelligence (AI) impacts green innovation in relation to sustainable development goals across 51 countries. Their findings reveal a strong positive correlation between AI and green innovation, emphasizing that AI is pivotal in driving environmental innovation.

Economic factors play a crucial role in the diffusion of green technologies. Studies have shown that economic incentives, such as subsidies, tax credits, and grants, significantly influence the adoption of renewable energy technologies. A study by Johnstone et al. (2010) indicates that economic incentives, such as subsidies, tax credits, and grants, significantly influence the adoption of renewable energy technologies. Shen et al. (2021) assess how setting economic growth targets influences regional green technology innovation. Their results conclude that targets significantly inhibit green technology innovation, with a stronger effect in cities with rapid economic growth and high target over-fulfillment.

In the same vein, Luo et al. (2024) analyze the effect of green technology innovation on economic growth in China, and the findings conclude that green technologies significantly boost GDP growth in China. Wang et al. (2023b) investigate how economic development pressure affects green total factor productivity in China's cities and methods. The findings indicate that economic growth impacts green technology progress and efficiency, with a stronger effect on progress. Moreover, Tsimisaraka et al. (2023) investigate the short-term and long-term effects of innovations and economic expansion with potential factors on CO_2 emissions, and the empirical findings indicate that innovations are positively associated with economic growth. Lastly, Ciccarelli and Marotta (2024) analyze the influence of climate change, environmental policies, and green innovation, and the findings provide evidence that disruptive effects are more severe in low-income, high-emission countries with limited environmental policies or high exposure to natural disasters.

Concerning the interactions between environmental policies and GTD, government policies, and regulations are pivotal in shaping the diffusion of green technologies. Policy instruments such as feed-in tariffs, renewable portfolio standards, and carbon pricing mechanisms have been shown to promote the adoption of renewable energy technologies, as studied by Hussain et al. (2022a). Moreover, Zhang et al. (2021) analyze the influence of public spending on green economic growth and energy efficiency in selected countries. They find that green economic growth fluctuates due to inconsistent government policies. Chen et al. (2022) explore the influence of environmental regulations on green technology innovation in Chinese cities. Their empirical findings show that governmental regulations on carbon emissions and air pollution positively influence green technology innovation, supporting the "Porter Hypothesis".

Likewise, Chen and Tanchangya (2022) explore the role of green technology and policy stringency on green growth in China. Their findings provide evidence that environmental policy stringency negatively affects green economic growth in the short term and shows no significant long-term effect. Another study by Afshan et al. (2023) assess the influence of green finance, eco-innovation, and environmental policy stringency on China's ecological footprint. The findings reveal that eco-innovation, green finance, and environmental policy stringency positively affect the ecological footprint. While recent studies have begun to explore the combination of ML with traditional econometric methods, such as the work by Nakano and Washizu (2022), which used neural networks to predict solar energy adoption in Japan, these approaches are still in their early stages, especially within the context of OECD economies.

Considering the ML approach, a few studies examine the relationship between the adoption and diffusion of green technologies and their potential related determinants. For instance, Magazzino et al. (2021) estimate the causal relationships among solar and wind energy production, coal consumption, economic expansion, and CO_2 emissions using advanced ML techniques. Their estimations reveal that while China and the US are expected to reduce CO_2 emissions due to increased renewable energy use, India is predicted to see a rise in emissions. Furthermore, Magazzino et al. (2021) investigate the relationships among Information and Communication Technologies (ICT) and environmental pollution in selected OECD countries through an ML algorithm. The ML findings confirm that ICT significantly contributes to CO_2 emissions. Another study by Peiró-Signes et al. (2022), employ an XGBoost model and ML methodologies to analyze the environmental orientation of innovative firms. Their estimation identifies the importance of policy regulations and managerial strategies in fostering an eco-innovative culture.

Recently, Zhou et al. (2024) forecast the impact of industrial robots on regional pollution in China. Their forecasting emphasizes that industrial robots significantly decrease pollution intensity across various provinces. Later, Aminullah, (2024) estimates the technology innovation and economic growth through system dynamics modeling. It highlights that link investments in General Purpose Technologies (GPTs) with industrial policy is crucial for inclusive growth and sustainable development, especially in the post-COVID-19 context. Furthermore, Zhao et al. (2024) investigate environmental quality utilizing panel data from 108 cities. Their findings reveal that green technological innovation significantly improves pollution reduction and carbon efficiency.

Furthermore, Sun et al. (2024) explore the forecasting of carbon pressure on low-carbon technological innovation in Chinese cities, utilizing random forest forecasting and ordinary least squares models. Their estimation supports that population size and economic development significantly promote low-carbon innovation. More importantly, previous studies (Hübler, 2011; Lee and Yang, 2018; Zhang et al., 2020; Bessi et al., 2021; Shahzad et al., 2022; Ahmad et al., 2023) also investigate the estimation of GTD by using ML approaches.

Despite the growing body of research on GTD, a significant gap remains in the application of advanced machine-learning techniques to predict the future spread of these technologies across

OECD economies. This study aims to fill this gap by integrating the ARIMA model into the forecasting process, providing a novel methodological approach that can enhance the accuracy and relevance of diffusion predictions. Additionally, by focusing on the specific context of OECD countries, this study offers insights that are directly applicable to policymakers in these nations, who are tasked with fostering green technology adoption as part of their sustainability agendas.

3. Data and Methodology

This study utilizes annual data from 1980 to 2022 for 38 OECD countries. These periods are chosen based on the data availability. GTD is based on patent applications from OECD statistics. This data provides insights into technological innovation and the frequency of new green technology inventions. Specifically, Figure 1 illustrates a time-series representation of overall GTD levels across OECD countries spanning from 1980 to 2022.

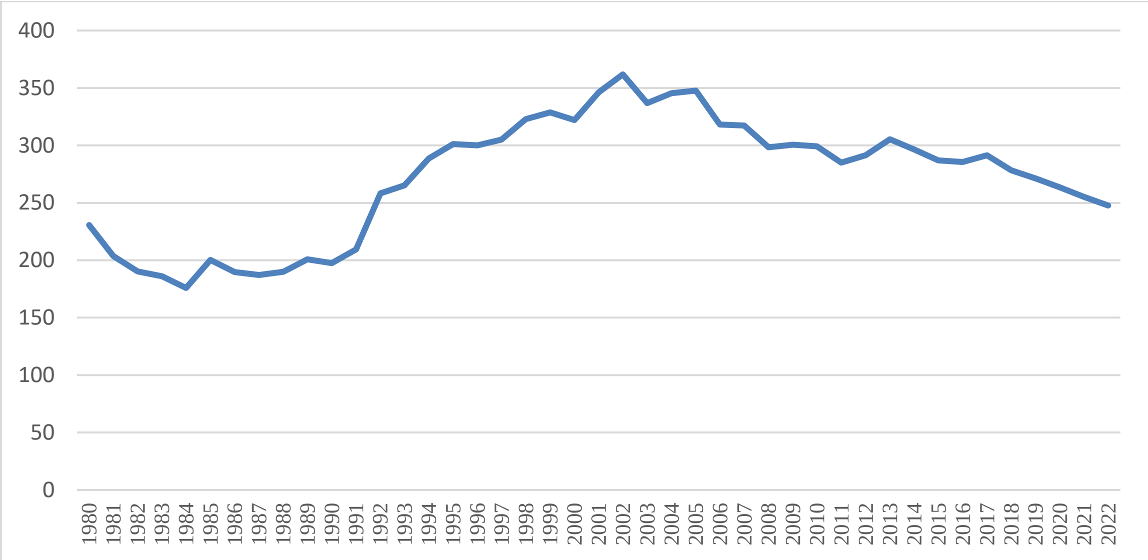

Figure 1. Green Technology Diffusion, 1980-2022

3.1. Machine Learning

ML is based on creating algorithms based on data on a given topic, updating outputs as new data becomes available, and using statistical analysis to predict outcomes. There are many different types of algorithms under ML that enable computers to learn. Computers extract a model from the learned data using various functions and statistical methods and can predict, predict, or classify new data according to this model. There are many different ML methods in the literature. These methods perform differently depending on the type of data. Therefore, it is difficult to say that one machine-learning method is superior to others. There are three basic stages in ML. These are:

1. Preparation of data: The first step is to prepare the right data, and the data needs to be prepared meticulously in order to reach the right results. At this stage, the data is made ready for processing by finding outliers, normalizing the data, etc. Depending on the type of problem, both numerical and symbolic (nominal) data can be processed.

2. Training: The second stage is to find the most appropriate model and train the data prepared in the first stage with this model. First, an ML method suitable for the problem is selected and the most appropriate model is created from the data by training. In order to find the appropriate model, as many models as possible should be built and tested. A part of the data in the training set is removed the model is validated and it is decided whether the model is appropriate or not.
3. Testing: The last stage is performance testing. For this, the model is tested by using the model created with data other than the training data used in the creation of the model. This data is called the test set. In the testing process, the performance of ML with the test set is measured by metrics such as accuracy rate, number of false positives, and number of true positives.

ML is used for classification, regression, and clustering, but it is also frequently used for time series analysis. ML and time series try to make new predictions based on information from the past. This is a type of supervised learning in ML. In this study, time series analysis is performed using ARIMA, an ML method known to give successful results.

3.2. Time Series Analysis

Time series analysis entails creating models that effectively represent or describe an observed time series, aiming to understand the underlying factors driving the observed patterns. The primary objective of time series analysis is to formulate mathematical models that can offer credible explanations based on the sample data. These models not only help in interpreting the historical data but also enable accurate forecasting, identifying trends, and understanding the temporal dynamics of the data, which can be applied to various fields.

3.3. Time Series Forecasting

The effectiveness of a time series forecasting model is measured by how well it predicts future values. This assessment can help clarify the reasons behind specific forecasts, interpret confidence intervals, or gain insights into the underlying issues. Time series data can be framed as a supervised learning problem. By using the previous time step as the input variable and the subsequent time step as the output variable, we can transform the time series dataset into a format suitable for supervised learning.

3.4. Forecasting Performance Measures

Time series forecasting performance metrics summarize the effectiveness and accuracy of the forecasting model. There are numerous metrics available for evaluation, and since time series forecasting usually involves predicting actual values—often categorized as regression problems—this paper will focus on metrics specifically designed to assess forecasts of real values.

3.5. Mean Absolute Error

The mean absolute error (MAE) is computed as the average of the forecast errors, with all error values treated as positive. This process, known as absolutizing, ensures that all errors are positive. An MAE of zero indicates perfect accuracy with no errors.

$$MAPE = \frac{\sum_{t=1}^{n} |(y_t - \hat{y}_t)/y_t|}{n} 100 \tag{1}$$

3.6. Mean Squared Error

The mean squared error (MSE) is determined by averaging the squared values of prediction errors. Squaring these errors ensures they are positive and disproportionately emphasizes larger errors. The error values are expressed in the squared units of the predictions. An MSE of zero signifies perfect accuracy or no error.

$$MSE = \frac{\sum_{t=1}^{n} (y_t - \hat{y}_t)^2}{n} \tag{2}$$

3.7. Root Mean Squared Error

The MSE, described earlier, is presented in squared units relative to the forecasts. To revert to the original units of the estimates, one can calculate the square root of the MSE, resulting in the root mean square error (RMSE). Like the MSE, an RMSE of zero indicates that there is no error.

$$RMSE = \sqrt{\frac{\sum_{t=1}^{n} |y_t - \hat{y}_t|}{n}} \tag{3}$$

3.8. Autoregressive Integrated Moving Average Model

The ARIMA model is a statistical approach used for analyzing and predicting time series data. ARIMA, short for ARIMA, combines three elements: autoregression, differencing, and moving averages. Specifically, it is a model that uses the dependent relationship between an observation and a set of lagged observations, AR (autoregression), I (integrated), differencing the raw observations, and MA (moving average) to stationary the time series. Forecasting with ARIMA usually consists of three main steps: identifying the temporal model, estimating the parameters, and diagnostic checking. The ARIMA model is denoted as (p, d, q), where each parameter is replaced with an integer to identify the specific ARIMA model used. The parameters are defined as follows: p is the number of lag observations in the model, also called the lag order; d is the number of differences applied to the raw data, known as the degree of differencing; and q is the size of the moving average window or the order of the moving average. To evaluate the model, forecasting metrics such as MAPE, MSE, and RMSE are employed. The ARIMA algorithm was repeatedly run using an optimization algorithm developed by the authors to create different models. An ARIMA model is evaluated by training it on a training dataset and testing its predictions on a test dataset.

In this study, we employ the ARIMA model, a robust machine-learning approach for time-series forecasting. The ARIMA model was chosen for its proven effectiveness in capturing temporal dependencies and trends within the data. Traditional econometric models, such as those used in prior studies (Bass, 1969; Lee and Song, 2007), often assume linear relationships and may not fully capture the nuances of technology adoption dynamics. ML models, including ARIMA, can model more complex relationships and interactions within the data, providing a more nuanced understanding of diffusion patterns. The use of ML also facilitates advanced analytical capabilities, such as pattern recognition and trend analysis.

The dataset is split into two parts: 66% is allocated for the initial training set, while the remaining 34% is used for testing. Each iteration produces a model that can predict new data. The iterative approach trains a new ARIMA model at each time step, with forecasts made and recorded in a list during each iteration. This process allows for comparing all predictions against the actual values at the end of the test set, enabling the calculation of an error score, specifically the RMSE. Time series forecasting models can generate predictions and also provide confidence intervals, which define the upper and lower bounds for the actual observations. These intervals are useful for assessing the range of potential outcomes and evaluating the model's accuracy.

The Estimate function permits the specification of the confidence interval, with the alpha argument in the prediction function determining the confidence level. By default, alpha is set to 0.05, corresponding to a 95% confidence interval. This confidence interval is considered both reasonable and widely accepted. An alpha of 0.05 implies that the ARIMA model will calculate the upper and lower bounds of the forecast such that there is only a 5% probability that the actual value will fall outside this range. This approach is essential for understanding the uncertainty associated with the model's predictions, ensuring that the forecast encompasses the true value most of the time. By adjusting the alpha value, users change the confidence level to meet specific requirements, allowing for greater flexibility in risk assessment and decision-making.

Once the predictions are made, it is necessary to measure the prediction success of the ML methods on the dataset. Performance metrics have been developed for these purposes. Prediction metrics such as MAPE, MSE, and RMSE are used to evaluate the model (Sammut and Webb, 2010). Lewis (1982) considered predictions with MAPE values below 10% as “very good”. For the sake of simplicity and completeness, this paper presents MAPE scores for comparison with model accuracy. To generate different models, the ARIMA algorithm was run repeatedly using the optimization algorithm developed by the author. After checking for efficiency issues, the most efficient model was used.

4. Empirical Findings

After the successful development of the model, visual representations of the results were created. Figure 1 provides sufficient evidence to validate the models discussed in this paper. It illustrates the forecasted emissions for both the current period (1980-2022) and the future period (2023-2037). Figure 2 includes shades of gray representing the confidence intervals (upper and lower bounds of the forecasts). Additionally, Table 1 presents the modeling error and accuracy metrics identified during the model development to offer a clearer understanding of the forecast values. Table 1 presents forecast values for GTD from 2023 to 2037 across OECD countries, along with accuracy metrics such as MAPE, RMSE, and MSE.

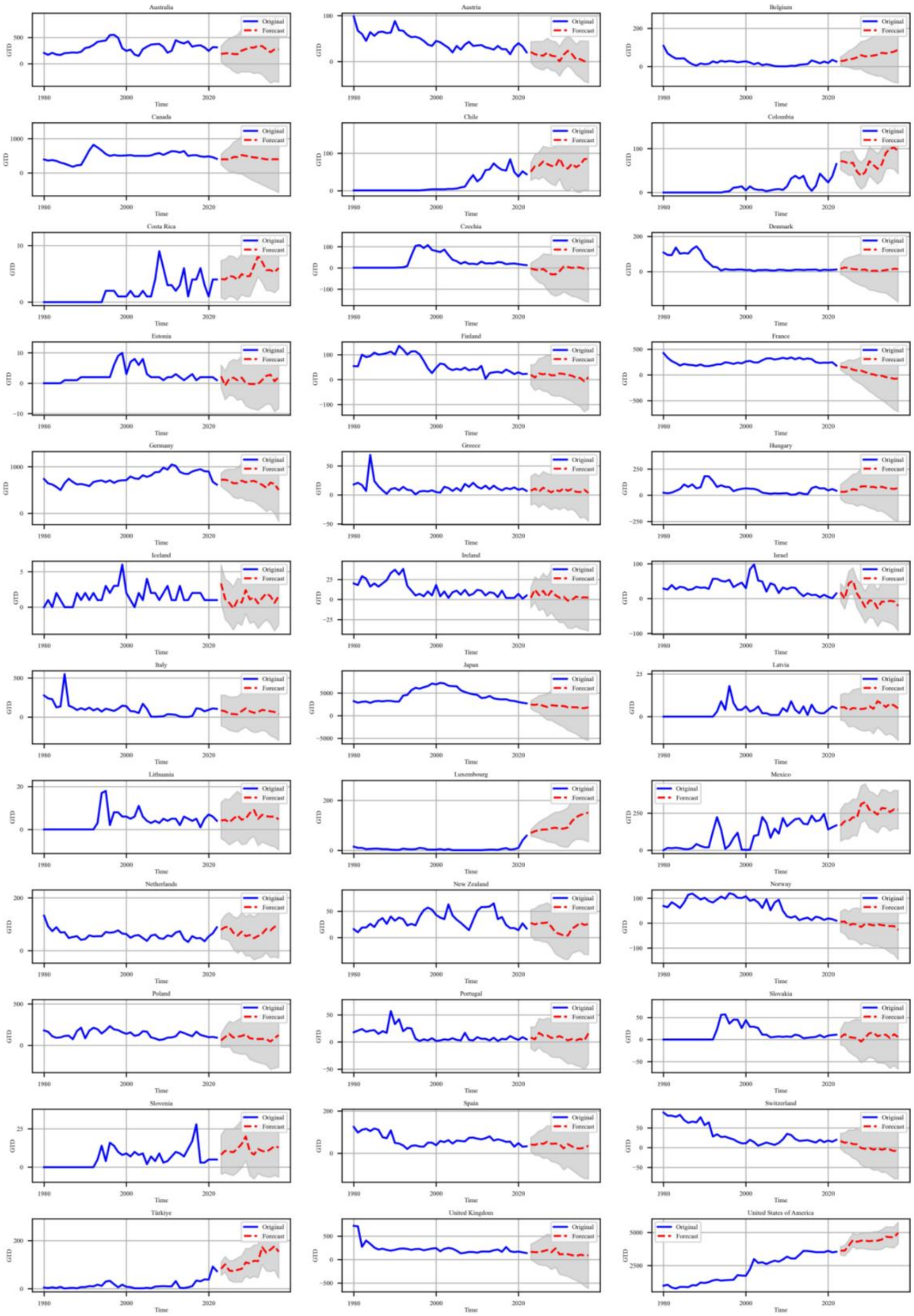

Figure 2. Green Technology Diffusion Estimates for 2023-2037

Table 1. Green Technology Diffusion Outlook from 2023 to 2037 in OECD Countries

Countries/Year	2023	2024	2025	2026	2027	2028	2029	2030	2031	2032	2033	2034	2035	2036	2037	MAPE	RMSE	MSE
Australia	188.03	195.65	203.94	184.87	182.32	249.63	277.05	308.02	306.18	343.5	333.87	275.25	219.65	272.37	272.91	21.99%	110.59	12229.15
Austria	20.85	16.03	14.19	12.7	19.27	12.8	11.33	0.59	14.95	23.39	16.35	4.52	5.38	0.8	-0.84	60.75%	21.76	473.61
Belgium	28.52	31	39.33	40.3	47.87	59.53	53.28	54.49	57.57	61.82	71.99	69.23	73.55	78.06	88.36	974.68%	43.31	1876
Canada	396.23	400.57	390.61	464.7	466.31	521.87	500.53	475.07	453.96	440.92	419.46	397.83	392.41	403.48	397.78	17.96%	114.61	13134.37
Chile	50.9	65.51	66.95	77.97	71.34	66.54	65.39	86.6	63.77	59.34	72.11	62.91	69.71	84.38	85.82	55.58%	25.75	662.82
Colombia	72.02	70.27	65.84	68.25	47.62	38.05	46.76	71.61	62.89	54.17	63.8	89.98	100.21	102.53	94.83	354.18%	48.63	2364.48
Costa Rica	4.09	4	4.62	4.5	3.96	4.94	4.59	4.6	6.36	8.13	7.08	5.66	5.66	5.3	6.02	103.73%	2.76	7.59
Czechia	-2.82	-7.53	-11.19	-4.71	-18.75	-30.26	-29.99	-14.94	6.27	4.53	-0.42	4.21	1.72	-3.41	-4.58	135.88%	30.74	944.78
Denmark	16.29	23.72	20.42	14.48	12.75	10.45	12.08	1.58	5.31	4.24	5.04	9.03	11.38	16.44	15.58	59.71%	6.89	47.4
Estonia	2.29	-0.72	1.5	1.84	0.97	1.86	0.07	-0.25	-0.25	-0.25	1.07	2.42	2.81	0.64	2.02	67.39%	1.42	2
Finland	19.23	8.39	24.32	20.91	25.35	16.53	17.64	24.52	22.42	19.38	15.36	7.24	6.79	-7.1	9.54	101.71%	20.13	405.05
France	165.93	148.37	150.96	102.39	87.12	85.08	56.1	26.59	11.61	-12.09	-13.76	-40.26	-53.62	-72.66	-67.81	90.52%	252.3	63653.07
Germany	720.89	720.81	697.89	646.22	647.77	702.13	666.64	687.12	696.6	657.17	612.46	549.61	659.08	629.7	502.13	25.61%	253.38	64200.55
Greece	7.33	10.99	5.66	12.61	8.21	4.53	9	6.34	11.46	7.24	10.13	5.4	4.96	9.06	3.51	40.94%	5.79	33.53
Hungary	33.22	32.07	42.28	58.58	51.93	84.5	85.28	78.25	79.83	69.95	81.29	69.45	64.71	59.76	68.07	263.62%	37.46	1402.97
Iceland	3.34	1.14	0.61	-0.17	0.96	0.64	2.39	1.09	1.4	0.54	1.3	1.93	1.55	0.61	1.56	72.28%	1.3	1.69
Ireland	2.05	12.33	5.34	10.75	3.26	10.47	5.35	2.04	3.45	-1.46	-0.56	3.59	2.08	2.72	2.22	70.43%	3.72	13.84
Israel	18.26	-0.21	43.78	51.48	14.38	-3.35	-24.58	-5.36	-6.64	-27.71	-8.5	-9.27	-6.32	-8.03	-20.79	225.41%	22.57	509.23
Italy	84.75	73.47	43.67	37.32	34.63	74.89	110.67	72.65	54.35	64.84	91.59	82.26	74.11	64	35.03	1477%	54.08	2925.05
Japan	2470.5	2399.8	2557.1	2203.9	1944.3	2321.7	2231.2	2171.3	2152.8	1875.8	1892.5	1875.3	1717.8	1686	1867.7	44.06%	1740.8	3030394
Latvia	5.51	5.52	3.69	5.07	4.73	4.42	4.76	6.12	4.63	9.08	7.57	5.64	7.5	6.6	4.86	133.15%	3.37	11.34
Lithuania	4.18	4.46	3.36	4.98	6.56	4.55	5.03	7.71	9.07	4.91	6.86	6.18	5.95	6.01	4.71	71.08%	2.34	5.49
Luxembourg	69.57	76.86	81.35	83.37	83.9	88.39	90.78	86.05	87.37	91.89	116.96	132.65	141.23	147.32	150.91	3676%	93.96	8828.5
Mexico	166.15	195.21	197.38	222.05	220.42	310.47	324.29	272.98	261.65	240.11	284.83	281.06	257.46	275.45	273.29	40.19%	80.17	6427.88
Netherlands	79.32	89.37	90.3	67.95	57.22	72.22	55.16	59.14	47.35	55.79	64.55	82.25	76.8	90.65	94.74	43.64%	24.37	594.02
New Zealand	27.81	24.85	27.66	27.48	28.58	20.74	9.74	6.88	3.83	3.67	16.74	21.71	27.89	23.9	25.75	57.82%	25.63	656.82
Norway	5.54	6.72	-8.72	-2.62	-5.31	-15.52	-2.81	-5.19	-9.14	-4.16	-7.7	-9.63	-11.83	-11.87	-27.02	154.69%	36.94	1364.61
Poland	59.53	100.47	138.79	93.57	105.22	112.25	132.74	85.54	77.71	76.19	77.2	74.61	45.86	85.98	124.65	29.10%	40.45	1636.23
Portugal	8.27	5.05	16.89	11.85	12.07	7.51	8.53	10.86	7.26	3.12	5.49	3.31	5.82	2.95	16.04	103.76%	5.57	31.05
Slovakia	5.01	12.08	5.83	4.27	3.32	-4.73	4.46	14.27	15.49	7.51	10.59	10.9	3.54	12.04	5.73	79.40%	6.37	40.64
Slovenia	8.13	10.74	10.15	9.81	12.17	15.1	20.08	10.24	8.24	11.82	10.59	10.13	11.79	13.66	12.91	121.29%	7.97	63.53
Spain	41.5	39.07	47.6	44.09	54.46	44.41	46.05	42.5	22.82	42.96	32.6	23.4	22.02	25.9	35.66	33.87%	23.5	552.28
Switzerland	16.83	12.52	14.01	9.06	8.43	-0.94	-2.92	-0.87	-5	-1.55	-5.11	-2.66	-4.97	-8.63	-4.91	99.84%	19.44	377.81
Türkiye	83	101.62	75.71	72.85	78.3	82.39	109.47	105.1	116.15	114.85	172.8	149.42	162.38	177.13	153.48	840.58%	93.22	8689.38
U.K.	165.76	158.48	158.61	180.09	203.88	156.22	239.01	113.78	116.31	115.97	95.21	74.29	103.46	90.55	91.81	27.55%	65.62	4305.47
USA	3624.9	3623.8	4004.8	4428.5	4294.6	4379.2	4376.9	4342.4	4377.7	4379.4	4464.1	4679.3	4646.1	4633.1	4970.4	30%	1025.7	1052075

High GTD Growth: Japan, Germany, and the United States exhibit high absolute values, suggesting significant investments and adoption rates in green technologies.

Moderate GTD Growth: Countries like Australia, Canada, and Mexico have shown steady but moderate increases in GTD over the years.

Low GTD Growth: Some countries, including Ireland, Iceland, Austria, Czechia, Latvia, Lithuania, Norway, Slovakia, Slovenia, Switzerland, Israel, Costa Rica, and Estonia, show low or even negative values in certain years, indicating potential challenges in adopting green technologies.

Furthermore, Table 1 displays the error metrics and accuracy parameters identified throughout the model development process. MAPE measures the accuracy of the forecast. Lower MAPE values indicate higher accuracy. For example, countries like Canada (17.96%), Australia (21.99%) and Germany (25.61%) have relatively low MAPE, indicating more reliable forecasts. In contrast, countries like Belgium (974.68%), Türkiye (840.58%), and Colombia (354.18%) have high MAPE values, suggesting less accurate predictions. RMSE provides the standard deviation of the residuals. Lower values indicate that the predictions are close to the actual data points Iceland (1.3), Estonia (1.42), and Lithuania (2.34) have low RMSE values, while Japan (1740.8), the USA (1125.7%), and Germany (253.38%) have a significantly high RMSE, pointing to larger prediction errors. MSE is the average of the squares of the errors. Countries like Ireland (1.69), Estonia (2), and Lithuania (5.49) have lower MSE values, whereas Japan (3030934), the USA (1052075) and Germany (64200.55) have extremely high MSE.

4.1. Discussion

The findings of the study indicate that Japan, Germany, and the USA will experience significant growth in GTD. This finding is consistent with recent studies highlighting these countries' leadership in green technology. For instance, a study by Jaffe et al. (2003) underscores the role of advanced research infrastructure and aggressive policy frameworks in these nations, which aligns with our results showing strong growth in green technology adoption. Furthermore, the work of Grübler et al. (1991) supports this observation, emphasizing that countries with substantial investments in innovation and supportive regulatory environments are likely to lead in technology diffusion.

On the other hand, countries like Australia, Canada, and Mexico are projected to see moderate increases in green technology adoption. This is consistent with recent research, such as that by Hascic et al. (2020), which found that while these countries have made significant strides in green technology, their progress is hampered by less aggressive policy measures and slower economic transitions compared to leading countries. Ireland and Iceland are forecasted to face challenges with low or negative growth in green technology adoption. This diverges from some recent studies, such as the one by Zeng et al. (2022), which suggested that smaller or less economically diverse countries might experience faster adoption rates due to less entrenched technologies. The results indicate that specific barriers, such as limited economic resources and less aggressive environmental policies, contribute to slower or stagnated growth in these countries.

5. Conclusion and Policy Implications

In this study, we have utilized advanced ML methodologies, particularly the ARIMA model, to forecast the diffusion of green technologies in OECD countries from 1980 to 2022 and 2023 to 2037. The dataset is divided into two segments: 66% is allocated for the initial training phase, while the remaining 34% is reserved for testing. The results of this study provide an overview of GTD forecasts for OECD countries from 2023 to 2037, highlighting growth trends and accuracy metrics. Countries like Japan, Germany, and the USA are expected to experience high GTD growth, while Australia, Canada, and Mexico show moderate increases. In contrast, countries such as Ireland and Iceland face challenges with low or negative GTD values. The accuracy of these forecasts is assessed using metrics like Mean Absolute Percentage Error (MAPE), RMSE, and MSE. Lower MAPE values (e.g., Canada 17.96%) and RMSE (e.g., Iceland 1.3) indicate more reliable predictions, whereas higher values (e.g., Belgium 974.68% MAPE and Japan 1740.8 RMSE) suggest less accurate forecasts.

The empirical findings based on the ARIMA model suggested that most countries display an increasing trend in GTD, indicating a positive outlook for green technology adoption over the forecast period. Based on these findings, countries such as Australia, Belgium, Canada, Czechia, Denmark, Finland, Greece, Hungary, Netherlands, Spain, and Slovakia show a consistent upward trend in GTD, reflecting stable progress in green technology adoption. On the other hand, countries like Mexico, Luxemburg, Türkiye, and the USA exhibit a steeper upward trend in GTD, suggesting more accelerated adoption rates, possibly due to recent policy shifts or increased investments in green technologies. In contrast, countries such as Austria, France, Japan, Germany, Finland, Norway, and Switzerland show a consistent downward trend in GTD, reflecting stable progress in green technology adoption. These countries have been early adopters of green technologies and have established robust frameworks and policies supporting environmental sustainability.

Most countries, including Colombia, Chile, Costa Rica, Estonia, Iceland, Ireland, Italy, Israel, Lithuania, Latvia, New Zealand, and Slovenia, display fluctuations in the forecasted GTD, which may imply variability in green technology adoption rates due to economic, political, environmental, and social factors. These fluctuations may be attributed to several factors. Economically, these countries might face budget constraints or shifting priorities that affect funding for green technologies. Politically, changes in government or policy directions can lead to inconsistent support for environmental initiatives. Environmentally, natural resource availability and environmental challenges influence the pace of green technology adoption. Socially, public awareness, cultural attitudes, and societal readiness for adopting new technologies can vary, causing uneven adoption rates.

Finally, the findings highlight the critical role of green technologies in addressing environmental challenges and promoting sustainable economic growth. The insights gained from this study underscore the importance of strategic planning and investment in green technologies to achieve long-term sustainability goals. Policymakers and stakeholders in OECD countries must prioritize the development and implementation of green technologies to foster economic resilience and environmental sustainability.

Drawing from these findings, this study offers policy recommendations to aid governments and policymakers in promoting environmental sustainability in the region and achieving the environmental targets outlined for sustainable development. Governments should increase investment in green technologies by providing financial support through subsidies, grants, and low-interest loans, accelerating the development and deployment of environmentally friendly solutions. Strengthening regulatory frameworks is essential, involving the enforcement of stricter emission standards, mandates for renewable energy usage, and penalties for non-compliance. Promoting public-private partnerships can enhance green technology dissemination through co-financing projects, risk-sharing, and knowledge exchange platforms. It is essential to invest in education and training initiatives to ready the workforce for green jobs, which involves revising curriculums and offering vocational training. Consumer adoption can be incentivized through tax rebates for electric vehicles, subsidies for solar panels, and awareness campaigns about green technologies. Supporting small and medium enterprises (SMEs) with financial aid, technical assistance, and market access for green products is vital for broader technology adoption. International cooperation and knowledge sharing through global agreements, collaborative research, and participation in environmental forums drive collective progress. Establishing robust monitoring and evaluation mechanisms to assess policy effectiveness, set clear targets, collect adoption data, and use ML models for future predictions will ensure continuous improvement. These recommendations enhance GTD in OECD countries, fostering sustainable economic growth and environmental preservation.

Although this study utilized the ARIMA model, future research should consider incorporating and comparing results with other ML models, such as neural networks, support vector machines, and ensemble methods. This provides a more robust and nuanced understanding of GTD trends. Secondly, the results of this study may not be applicable to developing countries in Africa or Asia due to their distinct economic characteristics. Therefore, future research should consider using datasets from these regions. Third, future studies could incorporate policy simulation and scenario analysis to evaluate the potential impacts of various policy interventions on GTD. By simulating different regulatory, financial, and social scenarios, policymakers can better understand the most effective strategies for accelerating green technology adoption.

One limitation of this study is the variability in the availability and quality of data across different countries. While comprehensive data on green technology adoption is available for some OECD countries, others may have incomplete or inconsistent data. This limitation can affect the accuracy and reliability of the forecasting models. The use of the ARIMA model relies on certain assumptions, such as linearity and stationarity in time-series data. While ARIMA is a powerful tool for forecasting, these assumptions may not fully capture the complex, non-linear dynamics of GTD.

Declaration of Research and Publication Ethics
This study does not require ethics committee approval and/or legal/private authorization is compatible with research and publication ethics.

Researcher’s Contribution Rate Declaration
The authors declare that they have contributed equally to the article.

Researcher's Conflict of Interest Declaration
There are no potential conflicts of interest in this study.

References

Afshan, S., Yaqoob, T., Meo, M.S. and Hamid, B. (2023). Can green finance, green technologies, and environmental policy stringency leverage sustainability in China: Evidence from quantile-ARDL estimation. *Environmental Science and Pollution Research*, 30(22), 61726–61740. https://doi.org/10.1007/s11356-023-26346-1

Ahmad, M., Kuldasheva, Z., Nasriddinov, F., Balbaa, M.E. and Fahlevi, M. (2023). Is achieving environmental sustainability dependent on information communication technology and globalization? Evidence from selected OECD countries. *Environmental Technology and Innovation*, 31, 103178. https://doi.org/10.1016/j.eti.2023.103178

Allan, C., Jaffe, A.B. and Sin, I. (2013). Diffusion of green technology: A survey. *International Review of Environmental and Resource Economics*, 7(1), 1–33. https://doi.org/10.1561/101.00000055

Aminullah, E. (2024). Forecasting of technology innovation and economic growth in Indonesia. *Technological Forecasting and Social Change*, 202, 123333. https://doi.org/10.1016/j.techfore.2024.123333

Bessi, A., Guidolin, M. and Manfredi, P. (2021). The role of gas on future perspectives of renewable energy diffusion: Bridging technology or lock-in? *Renewable and Sustainable Energy Reviews*, 152, 111673. https://doi.org/10.1016/j.rser.2021.111673

Chen, L. and Tanchangya, P. (2022). Analyzing the role of environmental technologies and environmental policy stringency on green growth in China. *Environmental Science and Pollution Research*, 29(37), 55630–55638. https://doi.org/10.1007/s11356-022-19673-2

Chen, Y., Yao, Z. and Zhong, K. (2022). Do environmental regulations of carbon emissions and air pollution foster green technology innovation: Evidence from China's prefecture-level cities. *Journal of Cleaner Production*, 350, 131537. https://doi.org/10.1016/J.JCLEPRO.2022.131537

Ciccarelli, M. and Marotta, F. (2024). Demand or supply? An empirical exploration of the effects of climate change on the macroeconomy. *Energy Economics*, 129, 107163. https://doi.org/10.1016/j.eneco.2023.107163

Cohen, F., Glachant, M., Söderholm, P. and Stephan, M. (2017). The impact of energy prices on the adoption of renewable energy: Lessons from the European Union. *Renewable Energy*, 105, 165-176. https://doi.org/10.1016/j.eneco.2017.10.020

Dewick, P., Green, K., Fleetwood, T. and Miozzo, M. (2006). Modelling creative destruction: Technological diffusion and industrial structure change to 2050. *Technological Forecasting and Social Change*, 73(9), 1084–1106. https://doi.org/10.1016/j.techfore.2006.04.002

Dutz, M.A. and Sharma, S. (2012). *Green growth, technology and innovation* (Policy Research Working Paper No. 5932). Retrieved from https://core.ac.uk/download/pdf/6419675.pdf

Grübler, A., Nakićenović, N. and Victor, D.G. (1999). Modeling technological change: Implications for the global environment. *Annual Review of Energy and the Environment*, 24(1), 545-569. https://doi.org/10.1146/annurev.energy.24.1.545

Habiba, U., Xinbang, C. and Anwar, A. (2022). Do green technology innovations, financial development, and renewable energy use help to curb carbon emissions? *Renewable Energy*, 193, 1082–1093. https://doi.org/10.1016/J.RENENE.2022.05.084

Hall, B. H. (2004). Innovation and diffusion. In J. Fagerberg and D.C. Mowery (Eds.), *The Oxford handbook of innovation* (pp. 459-484). https://doi.org/10.1093/oxfordhb/9780199286805.003.0017

Hall, B. H. and Khan, B. (2003). *Adoption of new technology* (NBRE Working Paper Series No. 9730). Retrieved from https://www.nber.org/system/files/working_papers/w9730/w9730.pdf

Han, C. and Yang, L. (2024). Financing and management strategies for expanding green development projects: A case study of energy corporation in China's renewable energy sector using machine learning (ML) modeling. *Sustainability*, 16(11), 4338. https://doi.org/10.3390/su16114338

Hao, L.N., Umar, M., Khan, Z. and Ali, W. (2021). Green growth and low carbon emission in G7 countries: How critical the network of environmental taxes, renewable energy and human capital is? *Science of the Total Environment*, 752, 141853. https://doi.org/10.1016/j.scitotenv.2020.141853

Haščič, I., Johnstone, N., Watson, F. and Kaminker, C. (2020). *Climate policy and technological innovation and transfer: An overview of trends and recent empirical results* (OECD Environment Working Papers No. 30). https://doi.org/10.1787/5km33bnggcd0-en

Hübler, M. (2011). Technology diffusion under contraction and convergence: A CGE analysis of China. *Energy Economics*, 33(1), 131–142. https://doi.org/10.1016/j.eneco.2010.09.002

Hussain, J., Lee, C.C. and Chen, Y. (2022a). Optimal green technology investment and emission reduction in emissions generating companies under the support of green bond and subsidy. *Technological Forecasting and Social Change*, 183, 121952. https://doi.org/10.1016/j.techfore.2022.121952

Hussain, Z., Mehmood, B., Khan, M.K. and Tsimisaraka, R.S.M. (2022b). Green growth, green technology, and environmental health: Evidence from high-GDP countries. *Frontiers in Public Health*, 9, 816697. https://doi.org/10.3389/fpubh.2021.816697

Jaffe, A.B., Newell, R.G. and Stavins, R.N. (2003). Technological change and the environment. In K-G. Mäler and J.R. Vincent (Eds.), *Handbook of environmental economics* (pp. 461-516). https://doi.org/10.1016/S1574-0099(03)01016-7

Johnstone, N., Haščič, I. and Popp, D. (2010). Renewable energy policies and technological innovation: Evidence based on patent counts. *Environmental and Resource Economics*, 45(1), 133-155. https://doi.org/10.1007/s10640-009-9309-1

Lee, J. and Yang, J.S. (2018). Government R&D investment decision-making in the energy sector: LCOE foresight model reveals what regression analysis cannot. *Energy Strategy Reviews*, 21, 1–15. https://doi.org/10.1016/j.esr.2018.04.003

Lin, B. and Ma, R. (2022). Green technology innovations, urban innovation environment and CO2 emission reduction in China: Fresh evidence from a partially linear functional-coefficient panel model. *Technological Forecasting and Social Change*, 176, 121434. https://doi.org/10.1016/J.TECHFORE.2021.121434

Luo, S. and Mabrouk, F. (2022). Nexus between natural resources, globalization and ecological sustainability in resource-rich countries: Dynamic role of green technology and environmental regulation. *Resources Policy*, 79, 103027. https://doi.org/10.1016/J.RESOURPOL.2022.103027

Luo, Z., Wang, C., Tang, Q. and Tian, W. (2024). Renewable energy technology innovation effect on the economics growth. *Chemistry and Technology of Fuels and Oils*, 59(6), 1271-1278. https://doi.org/10.1007/s10553-024-01644-7

Lv, C., Shao, C. and Lee, C.C. (2021). Green technology innovation and financial development: Do environmental regulation and innovation output matter? *Energy Economics*, 98, 105237. https://doi.org/10.1016/j.eneco.2021.105237

Magazzino, C., Mele, M. and Schneider, N. (2021). A machine learning approach on the relationship among solar and wind energy production, coal consumption, GDP, and CO2 emissions. *Renewable Energy*, 167, 99-115. https://doi.org/10.1016/j.renene.2020.11.050

Magazzino, C., Mele, M., Morelli, G. and Schneider, N. (2021). The nexus between information technology and environmental pollution: Application of a new machine learning algorithm to OECD countries. *Utilities Policy*, 72, 101256. https://doi.org/10.1016/j.jup.2021.101256

Maiti, M. (2022). Does improvement in green growth influence the development of environmental related technology? *Innovation and Green Development*, 1(2), 100008. https://doi.org/10.1016/j.igd.2022.100008

Meng, F., Xu, Y. and Zhao, G. (2020). Environmental regulations, green innovation and intelligent upgrading of manufacturing enterprises: Evidence from China. *Scientific Reports*, 10(1), 14485. https://doi.org/10.1038/s41598-020-71423-x

Nakano, S. and Washizu, A. (2022). A study on energy tax reform for carbon pricing using an input-output table for the analysis of a next-generation energy system. *Energies*, 15, 2162. https://doi.org/10.3390/en15062162

Oyebanji, M.O. and Kirikkaleli, D. (2023). Green technology, green electricity, and environmental sustainability in Western European countries. *Environmental Science and Pollution Research*, 30(13), 38525–38534. https://doi.org/10.1007/s11356-022-24793-w

Peiró-Signes, Á., Segarra-Oña, M., Trull-Domínguez, Ó. and Sánchez-Planelles, J. (2022). Exposing the ideal combination of endogenous–exogenous drivers for companies' ecoinnovative orientation: Results from machine-learning methods. *Socio-Economic Planning Sciences*, 79, 101145. https://doi.org/10.1016/j.seps.2021.101145

Popp, D. (2006). International innovation and diffusion of air pollution control technologies: The effects of NOX and SO2 regulation in the US, Japan, and Germany. *Journal of Environmental Economics and Management*, 51(1), 46-71. https://doi.org/10.1016/j.jeem.2005.04.006

Rao, K.U. and Kishore, V.V.N. (2010). A review of technology diffusion models with special reference to renewable energy technologies. *Renewable and Sustainable Energy Reviews,* 14(3), 1070–1078. https://doi.org/10.1016/j.rser.2009.11.007

Rogers, E.M. (2003). *Diffusion of innovations* (5th ed.). New York: Free Press.

Sadiq, M., Chau, K.Y., Ha, N.T.T., Phan, T.T.H., Ngo, T.Q. and Huy, P.Q. (2023). The impact of green finance, eco-innovation, renewable energy and carbon taxes on CO2 emissions in BRICS countries: Evidence from CS ARDL estimation. *Geoscience Frontiers,* 101689. https://doi.org/10.1016/J.GSF.2023.101689

Shahzad, M., Qu, Y., Rehman, S.U. and Zafar, A.U. (2022). Adoption of green innovation technology to accelerate sustainable development among manufacturing industry. *Journal of Innovation and Knowledge,* 7(4), 100231. https://doi.org/10.1016/j.jik.2022.100231

Shen, F., Liu, B., Luo, F., Wu, C., Chen, H. and Wei, W. (2021). The effect of economic growth target constraints on green technology innovation. *Journal of Environmental Management*, 292, 112765. https://doi.org/10.1016/j.jenvman.2021.112765

Sun, Q., Chen, H., Wang, Y., Wang, X., Peng, X., Zhang, Q. and Sun, Y. (2024). Does environmental carbon pressure lead to low-carbon technology innovation? Empirical evidence from Chinese cities based on satellite remote sensing and machine learning. *Computers and Industrial Engineering*, 189, 109948. https://doi.org/10.1016/j.cie.2024.109948

Sun, Y., Li, H., Andlib, Z. and Genie, M.G. (2022). How do renewable energy and urbanization cause carbon emissions? Evidence from advanced panel estimation techniques. *Renewable Energy*, 185, 996–1005. https://doi.org/10.1016/j.renene.2021.12.112

Tornatzky, L.G. and Fleischer, M. (1990). *The processes of technological innovation.* Maryland: Lexington Books.

Tsimisaraka, R.S.M., Xiang, L., Andrianarivo, A.R.N.A., Josoa, E.Z., Khan, N., Hanif, M.S., … Limongi, R. (2023). Impact of financial inclusion, globalization, renewable energy, ICT, and economic growth on CO2 emission in OBOR countries. *Sustainability,* 15(8), 6534. https://doi.org/10.3390/su15086534

Tuganova, R., Permyakova, A., Kuznetsova, A., Rakhmanova, K., Monzul, N., Uvarov, R., … Budennyy, S. (2022). Relationships between patenting trends and research activity for green energy technologies. *arXiv e-prints, arXiv-2010.* Retrieved from http://arxiv.org/abs/2210.09611

UNFCCC. (2015). *T*he Paris Agreement. United Nations framework convention on climate change. Retrieved from https://unfccc.int/process-and-meetings/the-paris-agreement

Wang, Q., Sun, T. and Li, R. (2023a). Does artificial intelligence promote green innovation? An assessment based on direct, indirect, spillover, and heterogeneity effects. *Energy & Environment.* https://doi.org/10.1177/0958305x231220520

Wang, S., Zhang, W., Wang, H., Wang, J. and Jiang, M.J. (2021). How does income inequality influence environmental regulation in the context of corruption? A panel threshold analysis based on Chinese provincial data. *International Journal of Environmental Research and Public Health*, 18(15), 8050. https://doi.org/10.3390/ijerph18158050

Wang, X., Li, J. and Wang, N. (2023). Are economic growth pressures inhibiting green total factor productivity growth? *Sustainability*, 15(6), 5239. https://doi.org/10.3390/su15065239

Xu, S.C., Li, Y.F., Zhang, J.N., Wang, Y., Ma, X.X., Liu, H.Y., … Tao, Y. (2021). Do foreign direct investment and environmental regulation improve green technology innovation? An empirical analysis based on panel data from the Chinese manufacturing industry. *Environmental Science and Pollution Research*, 28(39), 55302–55314. https://doi.org/10.1007/s11356-021-14648-1

Zeng, S., Tanveer, A., Fu, X., Gu, Y. and Irfan, M. (2022). Modeling the influence of critical factors on the adoption of green energy technologies. *Renewable and Sustainable Energy Reviews*, 168, 112817. https://doi.org/10.1016/j.rser.2022.112817

Zhang, D., Mohsin, M., Rasheed, A.K., Chang, Y. and Taghizadeh-Hesary, F. (2021). Public spending and green economic growth in BRI region: Mediating role of green finance. *Energy Policy*, 153(1), 112256. https://doi.org/10.1016/j.enpol.2021.112256

Zhang, S., Bauer, N., Yin, G. and Xie, X. (2020). Technology learning and diffusion at the global and local scales: A modeling exercise in the REMIND model. *Technological Forecasting and Social Change*, 151, 119765. https://doi.org/10.1016/j.techfore.2019.119765

Zhao, Q., Jiang, M., Zhao, Z., Liu, F. and Zhou, L. (2024). The impact of green innovation on carbon reduction efficiency in China: Evidence from machine learning validation. *Energy Economics*, 133, 107525. https://doi.org/10.1016/j.eneco.2024.107525

Zhou, P., Abbas, J., Najam, H. and Alvarez-Otero, S. (2023). Nexus of renewable energy output, green technological innovation, and financial development for carbon neutrality of Asian emerging economies. *Sustainable Energy Technologies and Assessments*, 58, 103371. https://doi.org/10.1016/J.SETA.2023.103371

Zhou, W., Zhuang, Y. and Chen, Y. (2024). How does artificial intelligence affect pollutant emissions by improving energy efficiency and developing green technology. *Energy Economics*, 131, 107355. https://doi.org/10.1016/j.eneco.2024.107355