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RESEARCH ARTICLE

Assessing the Impact of Private Investment in AI and Financial Globalization on Load Capacity Factor: Evidence from United States

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Abstract
The need for sustainable solutions has increased globally as a result of the growing environmental problems brought about by urbanization and industrialization. Given this, private investment in artificial intelligence (AI) has become a viable means of promoting environmental sustainability, mainly because of AI's capacity to minimize ecological footprints and maximize resource utilization. This research investigates the role of private investment in AI in promoting environmental sustainability in the United States from 1990 to 2019. It also analyzes the impact of financial globalization, technological innovation, and urbanization by testing the Load Capacity Curve (LCC) hypothesis. The research utilizes stationarity tests, which indicate that the variables are free from unit root problems and exhibit mixed orders of integration. Using the Autoregressive Distributive Lag (ARDL) Model bound test, the analysis finds that the variables are cointegrated in the long run. The short-run and long-run estimations of the ARDL model confirm the existence of the LCC hypothesis in the United States, revealing a U-shaped association between income and load capacity factor. The findings show that private investment in AI has a significant positive correlation with the load capacity factor, thus promoting environmental sustainability. Conversely, technological innovation and financial globalization exhibit a negative correlation with the load capacity factor in both the short and long run. To validate the ARDL estimation approach, the study employs Fully Modified OLS, Dynamic OLS, and Canonical Correlation Regression estimation methods, all of which support the ARDL outcomes. Additionally, the Granger Causality test reveals a unidirectional causal connection from private investment in AI, financial globalization, economic growth, technological innovation, and urbanization to the load capacity factor.

Keywords: Financial Globalization; LCC Hypothesis; Private Investment in AI; Technological Innovation; United States

Introduction

The devastation of the surroundings counts for the greatest pressing issues happening in the modern world today (Raihan et al.,2024; Li et al.,2021; Liu et al., 2021). This is due to its adverse effects on the overall economy, biodiversity, the atmosphere, human health, the quality of the air, and assets, including groundwater, soil, and forests (Rehman et al., 2021). Globally, maintaining economic growth and reducing climate change now depend on reducing CO_2 emission levels and maintaining ecological integrity (Raihan et al., 2022; Abir, 2024). Moreover, a great deal of this emission originates from a few nations (Magazzino et al., 2020). Even though the US economy has been expanding for over three decades, the nation is dealing with major environmental problems (Koondhar et al., 2018). As of right now, China is the nation with the fastest pace of economic growth, with the United States standing in second (He and Richard 2010). Even though China accounts for 28% of global CO_2 emissions, the USA is responsible for 16%, the EU for 11%, India for 6%, and other countries for 39%. However, as China has a population four times that of the USA, the USA has higher CO_2 emissions per capita than China (Koondhar et al., 2018). Moreover, according to 2020 year-end data (WorldBank, 2021), the USA produces almost 14%. These alarming figures underscore the relevance of the present research from a US perspective. Significant outcomes can be obtained by utilizing relevant factors, including financial globalization, technical innovation, and private investment in AI. The research findings can be implemented by policymakers to ensure a green environment in the USA. The effect of multiple socio-economic and technical variables on carbon emissions has been a focus of numerous research (Orhan et al., 2021; Su et al., 2021; Zhang et al., 2021; Guloglu et al.,2023 and Raihan et al.,2023). Even if CO_2 pollutions make up a sizable amount of greenhouse gases, Akinsola et al. (2021) claimed that carbon emissions are insufficient to accurately depict and assess total environmental damage. Conversely, the ecological footprint (EFP) was primarily initiated by Rees (1992), and it was subsequently emphasized by Galli et al. (2012) as the foremost for both financial and environmental indicators for evaluating ecological damage. In spite of this, not much research has been done on the Load Capacity Curve (LCC) concept. Therefore, the available literature fails to have information regarding the LCC hypothesis's validity in emerging economies like the USA. To close this gap, this research assesses the LCC hypothesis's relevancy to the USA. According to Siche et al. (2010), the load capacity factor (LCF) offers a more precise sustainability measurement. The LCF illustrates how strong or able a country is to support its citizens according to their modern lifestyles (Xu et al., 2022,). Therefore, an ecosystem is considered to be hampered when the LCF is less than 1 and sustainable when the LCF is greater than 1 (Pata et al., 2021; Sohail et al.2018a).

We have recently witnessed revolutionary developments in several industries as Artificial Intelligence (AI) has become increasingly integrated, and the environment field is no exception. Worldwide green growth issues can be resolved somewhat by the progress of AI technologies. Moreover, the implementation of AI can lower emissions to the environment (Shang et al.,2024). AI boosts Chinese industries' environmental sustainability and dramatically lowers the intensity of pollutant emissions (Cheng et al., 2024). Artificial intelligence-driven commercialization might reach to $3.9 trillion in 2022, up from $1.2 trillion in 2018, which marked a 70% growth from 2017 (Brown, 2013; Fatorachian and Kazemi, 2018; Richards et al., 2019). The public sector's contribution to AI has been expanding over the past few decades, as seen by the $3.2 billion in investments made by the U.S. government in 2022 (JEC,2023). Additionally, in almost 65% of AI-enabled environmental initiatives, mathematical models are used. All environmental professionals are likely to gain numerous advantages from AI tools (Konya and Nematzadeh, 2024). It can assist policymakers in formulating scientifically grounded strategies and plans for green ecosystems (Asadnia et al.,2014; Asadnia et al.,2017; Farahnakian et al., 2011). AI-driven technologies are crucial for ecological resource conservation as they facilitate the monitoring and preservation of natural habitats, animal populations, and ecosystems (Krishnamoorthy and Sistla, 2023; Sohail et al.2018b). To discover biodiversity hotspots, monitor endangered species, and identify threats to the environment like deforestation, poaching, and pollution, machine learning algorithms can examine satellite images, sensor data, and ecological parameters (Krishnamoorthy and Sistla, 2023). Stakeholders can safeguard biodiversity and ecosystem services by implementing focused interventions and making educated decisions by utilizing AI for environmental monitoring and conservation (Sistla and Konidena, 2023).

There are several ways in which the process of economic growth might result in environmental damage (Kartal et al., 2022). Growth in the economy comes with a substantial consumption of energy, natural assets, and production inputs, which initially pollutes the environment and puts more strain on it (Nurgazina et al., 2022). With time, the pressure on the ecosystem declines, and as environmental knowledge and demand grow, higher income levels help to improve natural health (Pata et al.,2023). On the other hand, in Bangladesh and Indonesia, Bakirtas et al. (2023) observed a reverse U-shaped link between GDP and LCF. In 2024, the US accounted for 13.3% of worldwide GDP and for around 4.21% of the global populace (World Bank, 2024). Meanwhile, almost 16% of global CO_2 emissions came from 5,416 MT of emissions in the United States (BP, 2020). Since the USA is one of the major polluters of greenhouse gases into the atmosphere, it bears some of the blame for the climate crisis and global warming. The catastrophic consequences of the United States' roughly 1.0 degree Celsius climate change are already worrisome, affecting the most vulnerable members of the population with a climate-fueled disaster that caused fatalities, deteriorating health, and the degradation of the natural world (Zhang et al.,2023, Sohail et al.2019). The majority of research has shown that the growing population causes more environmental damage (Voumik and Ridwan, 2023; Khan et al., 2021; Pham et al., 2020; Menz and Welsch, 2012). Financial globalization (FGOB) considers characteristics such as international assets and liabilities, FDI, investment portfolios, and related laws to assess how far a nation has incorporated into the global financial system. As a result, FGOB is a noteworthy measure of financial progress (Dhingra, 2023; Wang et al., 2023). With the progress of financial globalization, foreign direct investment is increasing globally. The most current UNCTAD (2020) showed that from $1.3 trillion in 2018 to $1.5 trillion in 2019, there was a 3.0% rise in worldwide FDI inflows. Scholars like Furceri et al. (2019), Usman et al. (2019), Obstfeld (2021), Gungor et al. (2021), and Awosusi et al. (2022) characterize FGOB as the convergence of global monetary systems into a single sector. Through the optimization of resources, clean energy, garbage disposal, prevention of pollution, and monitoring of the atmosphere, technological innovation can slow down the decline of the environment (Ha 2022; Vyas et al. 2022; Ramzan et al. 2023).

Consequently, our investigation makes multiple significant enhancements to the collection of contemporary literature. First of all, from a U.S. viewpoint, it addresses the largely unexplored field of private investment in AI, which makes it distinctive. The experimental research has presented consistent results concerning the correlation between LCF and private AI investment (PAI). Our study aims to clarify the linkages between LCF and PAI in light of the situation described above, offering additional relevant data for designing green policies. Second, the study makes use of unique PAI data that is categorized as Estimated Investment in AI (US$) and is adapted from Our World in Data. Within the framework of the USA's LCF, this analysis focuses on the trends and key research areas of private investment in artificial intelligence (AI), financial globalization, technical innovation, economic development, and urbanization. Analyzing the LCF within the context of the USA will offer fresh perspectives to scholars exploring the issue and establish a noteworthy contribution to the body of understanding. As far as we are aware, our work is the first to conduct a detailed representation of the literature on the LCF, enabling us to embark on the following research goals: What effect do PAI and FGOB have on the USA's LCF? In what ways can independent and dependent variables interact spontaneously? Furthermore, how do TI, GDP, and URBA affect the LCF? The significance of this research lies in the fact that private investment in artificial intelligence and financial globalization has not been extensively studied in other studies. By recognizing these elements, policymakers and strategy developers might be able to more effectively promote environmentally responsible behavior. More research in this area is essential to building a pleasant and sustainable environment, particularly in light of increasing interest in green cities and public awareness of ecological issues. The implications of GDP, PAI, FGOB, TI, and URBA on the LCF are examined in inquiry using ARDL methodologies from 1990 to 2018. Additionally, the robustness of the findings was analyzed as well using the FMOLS, DOLS, and CCR examinations. This study delivers valuable insights for legislators in the USA and other nations to achieve the SDGs while simultaneously promoting sustainable economic growth and increasing the ecosystem condition (as evaluated by the LCF) by adopting an integrative approach to the issue.

The paper checks the body of investigation on the chosen determinants in the second part. The information, theoretical framework, empirical model development, and estimating methods used to conduct the study are all covered in detail in the "Methodology" section. "Results and Discussion," the fourth part, offers an extensive discussion of the model's findings. The fifth and last part summarizes the analysis and suggested strategies of action.

Literature Review

The consequences of financial globalization, advancements in technology, and GDP development on the LCF have been the subject of several empirical investigations. While numerous analyses examined the ARDL model, the majority of papers focused on how trade openness, urbanization, and green energy usage affect environmental quality. Others have focused on analyzing the connection between trade openness, globalization, economic expansion, and LCF. Previous studies on the concept of ecological degradation in the context of the USA have not yet been extensively conducted as this is a relatively new field. However, the investigation used some prior studies that assisted with the selection of variables and methods. This section will cover a few of these inquiries.

GDP and Load Capacity Factor Nexus

The relationship between GDP development and ecosystem sustainability has been the subject of several studies. Many believe that as the economy grows, there will be an increase in CO_2 emissions. However, things become more complicated when we include load capacity in addition to CO_2 emissions as environmental quality criteria. People's goals for monetary progress encourage them to use all available energy resources, which has an economic effect of producing emissions (Panel et al., 2011). In addition, when business activity expands to achieve incredible growth, natural resource depletion takes place (Teng et al.,2024). Thus, the deterioration of biocapacity, biodiversity, and the LCF in different areas can be linked to carbon emissions and resource depletion for income development (Zhang et al., 2022). In Pakistan, Ali et al. (2023) performed an experiment using a "dynamic autoregressive distributed lags model" and a unique approach called "Kernel-based regularized least squares (KRLS)." They discovered an unexpected negative correlation (-0.270) between the load capacity factor and GDP development over a longer period. According to Pata (2021), growth in GDP significantly degrades the environment in a manner that cannot be balanced by clean power sources or increased medical expenses in the United States. Similar research (Fareed et al., 2021; Huilan et al.,2022; Shang et al., 2022; Abdulmagid Basheer Agila et al., 2022; Jin and Huang.,2023; ÇAMKAYA and KARAASLAN.,2024) that used the LCF and discovered that upsurges in GDP growth exhibited negative consequences on the LCF indicating the destruction of the ecosystem. By examining the consequences of GDP, Li et al. (2023) seek to understand how the next eleven countries improved their LCF between 1990 and 2018. The long-term outcomes illustrate that reliance on economic growth reduced LCF. However, Ullah et al. (2023) insist that while there is no short-term effect, growth in monetary complexity has a positive long-term consequence on LCF. On the other hand, a U-shaped connection between income and the state of the environment was observed by Guloglu et al. (2023), confirming the validity of the LCC theory.

AI Innovation and Load Capacity Factor Nexus

The increasing prevalence of artificial intelligence (AI) technology in our daily lives has extensive political and socioeconomic implications. Both officially and privately funded AI research and applications are encouraged heavily (Brandusescu, 2022). Negi (2018) focuses on the flow of investment in artificial intelligence from the top three major nations in the field: China, India, and the United States. They display the steps that the government has taken to incorporate artificial intelligence into its present ecosystem, which is supported by the private sector. The t-test demonstrates a significant relationship between annual investment and trend analysis, which suggests that the AI industry is growing quickly. Vietnam is seeing a relatively small amount of misdirected AI investment. Vietnam excessively remains significantly behind other Southeast Asian nations, necessitating both governmental and private investment in this sector (Pham et al.,2024). Artificial intelligence (AI) investment from the private sector has an enormous impact on the environment, positive as well as negative. AI helps with the preservation of natural assets, controlling energy consumption, ecological safeguarding, pollution control, agriculture, and other areas, all of which are critical to attaining environmental sustainability (Kumari and Pandey,2023). In the same way, Habila et al. (2023) indicate that the use of AI improves the human capacity to manage climate change to achieve sustainability while utilizing natural resources. Conversely, Okengwu et al. (2023) expressed that increased usage of AI in agriculture results in increased carbon emissions that affect humanity and the natural world. Green AI can boost productivity and alleviate its negative effects on the environment (Pachot and Patissier, 2022). Since private investment in AI usually has a negative impact on the natural world, government officials need to advocate for increased private investment, particularly in green AI.

Financial Globalization and Load Capacity Factor Nexus

Financial globalization is the uncontrolled and easy movement of financial resources within national boundaries (Kose et al., 2009). Both positive and negative effects of financial globalization on the LCF are apparent in emerging countries. In the case of India, Akadiri et al. (2022) demonstrated that FGOB is positively connected with the LCF both in the short and long run. According to Raihan et al. (2021), the short- and long-term consequences of FGOB are favorable for the LCF. By taking into account financial globalization over the years 1980–2021, Ozcan et al. (2024) aim to look at how Germany’s natural world is impacted. Through the use of advanced quantile-based methods, they highlight how FGOB boosts the quality of biodiversity. Moreover, using panel econometric approaches, Wang et al. (2022) scrutinized the most recent yearly data set that included 31 OBOR countries from 1996 to 2018. According to the findings, the environment deteriorates due to financial globalization. Many scholars also agree that FGOB slows down environmental damage by increasing the LCF (Jin et al.,2023; Xu et al.,2022; Pata et al.,2021; Yang et al.,2023). However, for Bangladesh, the effects of financial globalization on the ecosystem are multifaceted and rely on several variables, including clean FDI and the consumption of clean energy (Murshed et al. 2021). From 1990 to 2017, Kihombo et al. (2022) checked out the link between environmental impact and financial globalization in some West Asian and Middle Eastern (WAME) territories. The result demonstrates that through lowering the ecological footprint, financial globalization contributes a major part in promoting environmental sustainability. Several outcomes were also observed by (Awosusi et al.,2022 Ulucak et al.,2020; Tahir et al.,2021), and they revealed an encouraging effect of FGOB on the LCF, indicating the enhancement of ecological condition. In light of these outcomes, it is essential to determine if financial globalization provides the USA with a comparable opportunity to boost its load capacity factor.

Technological Innovation and Load Capacity Factor Nexus

Previous investigations have mostly overlooked technological innovation (TI), and it has been found to have both positive and negative outcomes. The continuous improvement in the degree of innovation has rendered policymakers, as well as scholars, to recognize the significance of technological innovation in preventing environmental deterioration (Du et al., 2022; Haldar and Sethi, 2022). Several analyses have been performed to analyze the fundamental connections between LCF and technological progress. The MMQR approach is used by Jahangir et al. (2024) to analyze the consequences of technological innovation on LCF between 1994 and 2018. The result illustrates that, in the top 10 SDG nations, TI has an adverse and substantial effect on lowering LCF. To examine how TI affects environmental quality in China, Kartal and Pata (2023) consider ecosystem indicators such as CO_2 pollution, EFP, and LCF. The findings exhibit that whereas TI reduces LCF at middle quantiles, it increases CO_2 emissions and ECF at higher quantiles. Some analyses also found that technological innovation is hazardous to the ecosystem (Raihan et al.,2024; Su et al.,2023; Adebayo et al.,2022). On the other hand, Wang et al. (2020) researched N-11 economies between 1990 and 2017, utilizing the unit root test, AMG, and CCEMG proposed by Pesaran (2007) serve as the foundation for the empirical estimations. The outcomes illustrate that TI has a destructive relationship with greenhouse gas emissions that boost the quality of the environment. Furthermore, Kihombo et al.(2021) assessed the implication of TI on environmental quality in West Asian and Middle Eastern countries and demonstrated that TI strengthens the natural world. Similarly to this, Rafique et al. (2020) provided evidence that technical advancements lower pollution in the BRICS countries. Multiple studies have also showcased the positive consequences of TI on maintaining financial sustainability (Mehmood et al.,2023; Khan et al.,2023; Anwar et al., 2021).

Urbanization and Load Capacity Factor Nexus

The goal for individuals shifting from rural to urban locations is to lead ordinary lives while working in industries that generate revenue (Ruel et al., 2008). Furthermore, the concept of the smart city, which advocates for energy from both renewable and nuclear sources, has emerged as the primary goal of industrialized and modern society (Chenic et al., 2022). The ARDL approach was utilized by Raihan et al. (2023) to examine cointegration and both short- and long-term dynamics using time series data from 1971 to 2018. The result illustrates that urbanization lowers Mexico’s LCF and, therefore, lowers the quality of the natural world. Urbanization has negative consequences on the dynamics of load capacity, which accelerates ecological deterioration (Teng et al.,2024). Using Cross-Sectional ARDL and AMG estimators, Shah et al. (2023) performed a study in the top 15 nations that produced natural gas and discovered that urbanization has a significant impact on environmental damage. Similarly, Raihan et al.(2024) and Caglar et al.(2023) also concluded that urbanization is harmful to the ecosystem. However, the relationship between urbanization and ecological sustainability is investigated by Fang et al. (2024) using the frequency domain causality technique and the ARDL estimator. The LCF curve theory is supported in Thailand as the ARDL estimator finding shows that urbanization reduces LCF. Zhu et al. (2018) came to the same conclusion that URB makes the natural world better. Additionally, Xu et al. (2022) assessed how urbanization affected the LCF in Brazil between 1970 and 2017. Surprisingly, the outcome of the ARDL approach revealed that the LCF is not affected by urbanization in Brazil. The same outcomes were given by Chen et al. (2022) using CCEMG and AMG tests for the years 1990–2019 and Haseeb et al. (2018) using FMOLS from 1995 to 2014, indicating that URB had no appreciable effect on the environment quality for the BRICS countries.

Research Gap

The relationships between load capacity factor, financial globalization, and private investment in AI, technological development, economic expansion, and urbanization in the USA have not, as far as we are aware, been investigated. Although researchers have looked into these areas on their own, they haven't consistently merged their discoveries. Previous research efforts demonstrated several shortcomings, especially an absence of comprehensive analyses of the connection between PAI and LCF in the USA. Private sector AI investments could aid agriculture, promote renewable energy, mitigate risks like oil spills, and develop sustainable practices, thereby reducing global warming risks. All of these aspects constitute PAI, an entirely new field to investigate from the perspective of the USA. To cover up these deficiencies, this study explores the link between PAI and the environment utilizing strong statistical approaches such as ARDL, FMOLS, DOLS, and CCR procedures. Through a review of these procedures, the USA might find out if harnessing technical innovation, monetary integration, and business growth can offer the possibility of elevating its load capacity factor and bringing it into line with broader global shifts toward improved environmental sustainability. The implications of the LCF in this area have not yet been the focus of inquiry. As a result, this investigation considers these components as essential to long-term environmental sustainability. By assisting stakeholders and lawmakers in establishing strategies that are customized to the distinctive ecological and socioeconomic situation of the United States, this analysis advances green improvement.

Methodology

Data and Variables

The ongoing research analyzed data to check out how technical advancements, financial globalization, GDP, urbanization, and private investment in AI influenced the USA's LCF between 1990 and 2019. The United States gathered attention because of its sustainability concerns and data accessibility. The World Development Index (WDI) is the source of the GDP and URBA figures. In this case, we take the LCF as an endogenous factor that derives from GFN and is utilized as a substitute for ecological sustainability. Our World in Data is the same source from which PAI and TI information was collected. Conversely, the FGOB info is adapted from the KOF Globalization Index. In addition, we selected FGOB, TI, and PAI as our investigation's policy variables.

Theoretical Framework

The most important instrument in the realm of the environmental field is the load capacity curve (LCC), which offers fascinating details on the complex links between ecological sustainability, economic success, and progress in humanity. This is significant as it illustrates the balance—or absence between the planet's capability of restoring its natural resources (biological capability) and the utilization of human capital (ecological footprint). Since biocapacity and EF are incorporated in the denominator of the LCF, a greater LCF is symbolic of a healthier environment (Pata and Kartal, 2023).
The LCF delivers a sophisticated ecological examination by contrasting biocapacity and ecological footprint (Dogan and Pata, 2022). Furthermore, the LCC highlights the interconnectedness of the world's biological issues, as claimed by Wu et al. (2023), including climate change, resource scarcity, and loss of biodiversity. It is believed that the LCC has a U-shaped connection, with GDP constituting the main driver. According to Pata and Tanriover (2023) and Pata and Ertugrul (2023), there are distinct trends in the implications of GDP on the environment, suggesting a U-shaped curve connection. The awareness that resource usage grows in tandem with economic

expansion and developments in personal wealth is highlighted by this relationship as a crucial aspect of ecological sustainability (Degirmenci & Aydin, 2024).

Table 1. Source and Description of Variables

Variables	Description	Logarithmic Form	Unit of Measurement	Source
LCF	Load Capacity Factor	LLCF	Gha per person	GFN
GDP	Gross Domestic Product	LGDP	GDP per capita (current US$)	WDI
PAI	Private Investment in AI	LPAI	Estimated Investment in AI (US$)	Our World in Data
FGOB	Financial Globalization	LFGOB	Globalization Index	KOF Globalization Index
TI	Technological Innovation	LTI	Patent applications, residents	Our World in Data
URBA	Urbanization	LURBA	Urban population (% of total population)	WDI

Globalization in finances promotes cross-border monetary activity, which elevates national manufacturing and, consequently, exacerbates ecological destruction (Xu et al.,2022; Ahmed et al.,2021). The findings by Caglar et al.(2023) validate the LCC concept by demonstrating that monetary eventually becomes an ecologically beneficial factor. As was previously indicated, there may be a range of linkages between the components, including GDP growth, technical innovation, private investment in AI, urbanization, financial globalization, and load capacity factor. To improve knowledge of previous research, we have created the following equation (1) for LCC theory:

$$Load\ Capacity\ Factor = f(GDP, Y_t) \qquad (1)$$

Here, Y_t is a variable for additional parameters impacting the LCF, while GDP is a variable for income in equation (1). Equation (2) seeks to provide a deeper comprehension of the factors impacting the LCF by including additional relevant variables such as urbanization, financial globalization, private investment in AI, and economic growth.

$$LCF = f(GDP, PAI, FGOB, TI, URBA) \qquad (2)$$

The load capacity factor in equation (2) is represented by LCF, whereas the terms financial globalization (FGOB), technological innovation (TI), urbanization (URBA), and private investment in artificial intelligence (PAI) are introduced to symbolize particular principles. The econometric explanation of equation (3) is given above.

$$LCF_{it} = \alpha_0 + \alpha_1 GDP_{it} + +\alpha_2 PAI_{it} + \alpha_3 FGOB_{it} + \alpha_4 TI_{it} + \alpha_5 URBA_{it} \quad (3)$$

Equation (4) illustrates the variables' logarithmic values. It increases understanding and facilitates the formulation of conclusions based on statistics by breaking down complicated connections into more straightforward linear forms. Logarithmic scales can manage data of various sizes and assist with heteroscedasticity when broad ranges need to be minimized.

$$LLCF_{it} = \alpha_0 + \alpha_1 LGDP_{it} + \alpha_2 LPAI_{it} + \alpha_3 LFGOB_{it} + \alpha_4 LTI_{it} + \alpha_{5L} URBA_{it} \quad (4)$$

Here, the research's coefficients are displayed in the parameter range of α_0 to α_6 in equation (4).

Econometric Framework

This investigation deployed the ARDL technique for data estimation to explore the link between LCF and variables like GDP growth, PAI, FGOB, TI, and URBA in the USA. We additionally adopted the FMOLS, DOLS, and CCR approaches to guarantee robustness. To ensure stationarity, the unit root examinations (ADF, P-P, and DF-GLS) were performed at the beginning of the study. Due to the nature of the time series data, the ARDL bound test was then implemented. The ARDL (both short run and long run) estimate was then carried out. Ultimately, after an elaborate estimating procedure, we determined which econometric model was the most efficient and trustworthy.

Unit Root test

To ensure consistency in information, a regression test was conducted to eliminate unit roots across all variables. This is important because factors involving unit roots or non-stationary data must assist in explaining a greater proportion of the results to prevent the drawing of incorrect conclusions (Nelson and Plosser, 1982; Engle and Granger, 1987). It is essential to use a unit root analysis to prevent incorrect regression. The stationary nature of the regression variables is confirmed by differences and stationary processes (Raihan et al., 2022). The empirical research's findings indicate that before applying cointegration approaches, the integration sequence must be examined (Sahoo and Sethi, 2022). A time series' stationarity or non-stationarity is calculated by Voumik and Ridwan (2023) since it is critical in identifying non-stationary data that might produce inaccurate results. To observe the stationarity within the data set, this research adopted the Dickey Fuller-Generalized Least Squares (Elliot et al., 1992) unit root test, the Philips Perron (Philips and Perron, 1968), and the Augmented Dickey-Fuller (Dickey and Fuller, 1979) unit root examination. Due to its ability to control serial autocorrelation, the ADF method has become more popular (Dickey and Fuller, 1981). Compared to the Dickey-Fuller (DF) approach, the ADF technique is more robust and applicable to more sophisticated procedures (Fuller, 2009). The purpose of applying these tests was to confirm that no parameter exceeded the integration order, corroborating the ARDL simulation's methodological coherence (Raihan,2024).

Autoregressive Distributive Lag Model

The ARDL test was developed by Pesaran et al. (2001) and widely utilized due to its robustness and adaptability in handling different degrees of variable integration. If the indicators are integrated at the I(0) or I(1) level, the ARDL Bounds testing method can be analyzed, in contrast to traditional cointegration assessments. This approach is beneficial even with a small sample size since it produces dependable and consistent estimates even when there are only a limited number of data points available (Ridzuan et al., 2023; Pattak et al.,2023). The longer-period connection among LCF, GDP, PAI, FGOB, TI, and URBA is shown by Formula (8). This method was created to assist in defining ARDL Bounds:

$$\Delta LLCF_t = \sigma_0 + \rho_1 LCF_{t-1} + \rho_2 LGDP_{t-1} + \rho_3 LPAI_{t=1} + \rho_4 LFGOB_{t-1} + \rho_5 LTI_{t-1} + \rho_6 LURBA_{t-1} + \sum_{i=1}^{w} \sigma_1 \, \Delta LLCF_{2_{\mathrm{t-i}}} + \sum_{i=1}^{w} \sigma_2 \, \Delta \mathrm{LGDP}_{\mathrm{t-i}} + \sum_{i=1}^{w} \sigma_3 \Delta LPAI_{t=1} + \sum_{i=1}^{w} \sigma_4 \, \Delta \, LFGOB_{t-i} + \sum_{i=1}^{w} \sigma_5 \Delta \mathrm{LTI}_{\mathrm{t-i}} + \sum_{i=1}^{w} \sigma_6 \Delta \mathrm{LURBA}_{\mathrm{t-i}} + \varepsilon_t \quad (4)$$

It is possible to conclude that the variables are long-term correlated if the F-statistics are greater than the highest critical value for rejecting the null hypothesis. If the F-statistic is smaller than the lowest allowable value, the null hypothesis is accepted. If the F-statistics are seen to be between the lowest and maximum limits, the test is considered inconclusive (Raihan et al.,2023). Equations 5 and 6 reveal the null and alternative hypotheses:

$$H_0 = \sigma_1 = \sigma_2 = \sigma_3 = \sigma_4 = \sigma_5 = \sigma_6 \quad (5)$$

$$H_1 = \sigma_1 \neq \sigma_2 \neq \sigma_3 \neq \sigma_4 \neq \sigma_5 \neq \sigma_6 \quad (6)$$

The signs "H0 and H1" denoted the null hypothesis and the alternative hypothesis, respectively.

Our research assessed the error correction model (ECM) after determining the long-term links to investigate the short-term behavior of the independent factors and the short-term adjustment rate toward the long-term rate (Luqman et al., 2021). To do this, the ECM is included in the ARDL structure, as shown in Equation (6)

$$\Delta LLCF_t = \sigma_0 + \sum_{i=1}^{w} \rho_1 \Delta \mathrm{LCF}_{\mathrm{t-i}} + \sum_{i=1}^{w} \rho_2 \Delta \mathrm{LGDP}_{\mathrm{t-i}} + \sum_{i=1}^{w} \rho_3 \Delta LPAI_{t=1} + \sum_{i=1}^{w} \rho_4 \Delta \, LFGOB_{t-i} + \sum_{i=1}^{w} \rho_5 \, \Delta \mathrm{LTI}_{\mathrm{t-i}} + \sum_{i=1}^{w} \rho_6 \Delta \mathrm{LURBA}_{\mathrm{t-i}} + \ell ECT_{t-i} + \varepsilon_t \quad (7)$$

Here, the notion ℓ is the rate of adjustment.

Robustness Check

The investigation scrutinized the FMOLS, DOLS, and CCR techniques to represent the long-run impact of GDP, PAI, FGOB, TI, and URBA on LCF in order to evaluate the stability within the ARDL long-term estimation. When there is evidence of series cointegration, FMOLS and DOLS can be utilized. However, the biggest advantage of the DOLS estimation is its ability to present different levels of integration of discrete elements inside the cointegrated framework (Pesaran, 1997; Raihan and Tuspekova, 2022). The FMOLS technique was established by Hansen and Phillips(1990). When addressing cointegration and its influence on autocorrelation and endogeneity in the explanatory variables, the FMOLS technique modifies the least squares approach (Pattak et al.,2023). The CCR technique was developed by Park (1992) and merely utilizes the static part of a lagged model to convert data. In a cointegrating system, the CCR ensures that data extracted from explanatory variables on unobserved heterogeneity will show at zero frequency. As a result, the CCR approach produces chi-square and arithmetically effective approximation assessments devoid of any undesirable aspects. We, therefore, use the FMOLS and DOLS estimators to determine elasticity over the long run. What follows is equivalent to the FMOLS equation, as shown in Exhibit 8.

$$\Delta LLCF_t = \sigma_0 + \sigma_1 LGDP_t + \sigma_2 LPAI_t + \sigma_3 LFGOB_t + \sigma_4 LTI_t + \sigma_5 LURBA_t + \sum_{i=1}^{w} \rho_1\, \Delta LLCF_{\mathrm{t-i}} + \sum_{i=1}^{w} \rho_2\, \Delta \mathrm{LGDP}_{\mathrm{t-i}} + \sum_{i=1}^{w} \rho_3 \Delta PAI_{t-1} + \sum_{i=1}^{w} \rho_4\, \Delta\, LFGOB_{t-i} + \sum_{i=1}^{w} \rho_5 \Delta \mathrm{LTI}_{\mathrm{t-i}} + \sum_{i=1}^{w} \rho_6 \Delta \mathrm{LURBA}_{\mathrm{t-i}} + \varepsilon_t \qquad (8)$$

Here, the longer-period flexibility is assessed using the FMOLS and CCR coefficients, and t shows the time-varying trend.

Pairwise Granger Causality test

The concept of a causality analysis aims to analyze whether or not previous changes in a factor are responsible for the present observation, as theoretical correlations may not hold in practice due to certain elements that may not be clearly described in theory (Voumik et al.,2023). This work employs the Pairwise Granger causality test, which is a statistical view of causation based on a prediction that offers multiple benefits over other time-series research methodologies (Winterhalder et al. 2005). To say that X is causally related to Y would be to say that the sum of X's prior and current values deviates substantially beyond 0. Y and X causality are subject to the same laws; if the results deviate from zero, it indicates the presence of causation on both sides. The analysis used the paired Granger causality test introduced by Granger (1969), to ascertain if there prevailed a short-term causal link between the components. Equation (9) shows that Xt and Yt are causally related.

$$E\left(Y_{t+h} \middle| J_{t,} X_t\right) = E(Y_{t+h}|J_t) \qquad (9)$$

Here, Jt notation is used for the sets of information gathered from all of the outcomes up to a certain point of time (t).

Diagnostic test

Several diagnostic tests were implemented in this research to confirm the data's heteroscedasticity, serial correlation, and normality. The Lagrange Multiplier (LM) test, the Jarque-Bera test (Jarque and Bera, 1987), and the Breusch-Pagan-Godfrey test (Breusch and Pagan, 1979) serve as essentials for validating model assumptions and guaranteeing the robustness of results in time series analysis. Since many econometric models assume normally distributed errors for successful inference, the Jarque-Bera examination checks the normality of residuals, a vital phase in the process. By detecting serial correlation in residuals, the Lagrange Multiplier test makes sure that errors do not correlate over time, which might result in misleading and biased estimations. The heteroscedasticity, or non-constant variance of residuals, is verified using the Breusch-Pagan-Godfrey assessment, which can lead to inaccurate standard errors and estimates.

Result and Discussion

The summary statistics for the variables we investigated with 32 observations are displayed in Table 02 below. The descriptive data for the USA for the following seven variables are provided (LLCF, LGDP, LGDPSQ, LPAI, LFGOB, LTI, and LURBA). As can be seen in the table, all of the factors we chose had a positive mean except LLCF, and the mean was the highest for LGDPSQ. Furthermore, the estimated standard deviations of each variable are quite small, implying that the data points are centered around the mean and have minimal periodic variability. Just LLCF and LPAI showcase positive skewness among the variables; in contrast, LGDP, LGDPSQ, LFGOB, LTI, and LURBA exhibit negative skewness. Furthermore, the Jarque-Bera normality examination was applied to ensure that each variable in this investigation had a normal distribution. Since this test accounts for both skewness and any anomalous Kurtosis, it seems logical. Key indicators of statistics, including mean, median, maximum, minimum, standard deviation, probability value, total, and sum square, are illustrated in Table 2, which offers an exhaustive analysis of the information at hand.

Table 2. Descriptive Statistics of Variables

Statistic	LCF	LGDP	$LGDP^2$	LPAI	LFGOB	LTI	LURBA
Mean	-0.835416	10.64393	113.3917	22.0143	4.290778	12.1409	4.377885
Median	-0.822656	10.71885	114.8942	21.2377	4.322086	12.27706	4.382195
Maximum	-0.63269	11.15938	124.5318	25.66873	4.385638	12.59584	4.417309
Minimum	-0.970971	10.08116	101.6297	20.55212	4.093117	11.38458	4.32148
Std. Dev.	0.093945	0.318778	6.76113	1.665446	0.091946	0.408947	0.027091
Skewness	0.065531	-0.255693	-0.219087	0.989543	-1.146481	-0.577478	-0.500595
Kurtosis	1.965479	1.888894	1.876795	2.466317	3.067511	1.90974	2.252894
Jarque-Bera	1.449882	1.994763	1.938117	5.602132	7.016314	3.363452	2.08073
Probability	0.484353	0.368844	0.37944	0.060745	0.029952	0.186053	0.353326
Sum	-26.73331	340.6058	3628.534	704.4575	137.3049	388.5089	140.0923
Sum Sq. Dev.	0.273596	3.150205	1417.099	85.98507	0.262076	5.184362	0.022751
Observations	32	32	32	32	32	32	32

In Table 3, all three stationarity tests (ADF, DF-GLS, and P-P) are demonstrated for log-transformed variables at both the level and first difference form. In each of the three unit root evaluations, it appears that only the urbanization factor is stationary at level I(0), while the load capacity factor, GDP, GDP squared, private investment in AI, financial globalization, and innovations in technology were non-stationary before we considered their first differences. This mixed sequence of integration encourages us to analyze the assessment now using the ARDL methodology.

Table 3. Results of the Stationarity test

Variables	ADF		P-P		DF-GLS		Decision
	I(0)	I(1)	I(0)	I(1)	I(0)	I(1)	
LLCF	-0.799	-5.347***	-0.826	-5.354***	-1.475	-4.302***	I(1)
LGDP	-0.878	-4.841***	-0.953	-4.829***	-1.771	-3.451***	I(1)
$LGDP^2$	-0.614	-5.000***	-0.650	-4.968***	-1.842	-3.423***	I(1)
LPAI	-0.806	-7.505***	-1.897	-7.403***	-0.933	-5.365***	I(1)
LFGOB	-2.132	-4.140***	-2.134	-4.090***	-1.943	-4.520***	I(1)
LTI	-2.015	-5.053***	-2.131	-5.076***	-0.946	-3.765***	I(1)
LURBA	-8.850***	-1.787	-5.120***	-1.743	-3.781***	-1.462	I(0)

To find confirmation of co-integration between the variables, the present research employed an ARDL bounds test approach. The null hypothesis that there exists no co-integration is rejected at the 1% significance level, based on the ARDL bound test findings. The critical value has been surpassed by the F test statistic result of 5.6945. Therefore, it can be claimed that the parameters of the model have certain co-integrating associations. According to this investigation, the long-term driving forces consist of urbanization, technological innovation, financial globalization, economic expansion, and private investment in artificial intelligence. These characteristics additionally motivate the system to respond first to a typical stochastic disruption. We conclude that the LCF in the United States is affected by differences in all of these variables.

Table 4. Results of ARDL bound test

	Test Statistics	Value	K	
	F statistics	5.6945	6	
	Significance level			
Critical Bounds	10%	5%	2.50%	1%
I(0)	1.99	2.27	2.55	2.88
I(1)	2.94	3.28	3.61	3.99

After the cointegration had been verified by the bound testing process, we might evaluate the long-term connection among those variables. Table 5 adopts the dynamic ARDL method to demonstrate the short and long-term consequences of LGDP, LGDP^2, LPAI, LFGOB, LTI, and LURBA on LLCF in the USA.

The findings indicate that the load capacity of the US environment seems to decrease with economic expansion over time but grows with the continued expansion of GDP. Urbanization and private investment in AI have been significant contributors to the expansion of load capacity factor, but long-term US LCF is decreased by financial globalization and technological innovation. Our findings demonstrate that the ecosystem gradually loses its natural qualities due to economic development. The US economy is expanding and strongly dependent on energy sources like fossil fuels, which cause ecological damage; therefore, the conclusion makes theoretical sense. The outcomes in Table 5 show that the LCF decreases by 3.449% in the long run and by 4.242% in the short run for each 1% expansion in GDP. Our analysis result agrees with previous studies that established an adverse link between GDP growth and LCF. A few studies have concluded that a boost in the GDP has detrimental implications for the environment. This includes Xu et al. (2022) for Brazil; Shang et al. (2022) for ASEAN countries; Pata and Balsalobre-Lorente (2022) for Turkey; Khan et al. (2023) in the context of G7 and E7 countries; Akadiri et al. (2022) for India; and Pata (2021) in Japan and the United States. However, for Taiwan, Yeh and Liao (2017) observed the inverse outcome. They also revealed that Taiwan has come to the point where financial pressures no longer adversely affect the natural world. Likewise, Nathaniel et al. (2020) identified no evidence linking economic expansion to environmental damage in CIVETS (Egypt, Turkey, South Africa, Indonesia, and Vietnam).

On the other hand, each unit of growth in GDP2 results in a 1.184% long-term and 0.156% short-term improvement in LCF. Given that the coefficient for LGDP is negative and the coefficient for LGDP^2 is positive, and both are statistically significant, this suggests that environmental pressure diminishes over time, supporting the recently proposed LCC hypothesis for the USA. The coefficients for LPAI indicate a positive correlation with LLCF, implying a 0.015% long-term degradation and a 0.462% short-term increase in LCF for every 1% rise in PAI. Thus, private investment in artificial intelligence in the United States significantly contributes to the green ecosystem. According to Karpovich et al. (2022), executing "green" investment-innovative projects in intelligent manufacturing operated by artificial intelligence plays an integral part in ensuring the ecological security of Russia's local economy. Moreover, based on Platon (2024), eco-investment and artificial intelligence constitute key elements that might accelerate and improve the circular economy.

Conversely, LCF is destructively connected with FGOB in both the long and short run, and this relationship is statistically significant. These findings suggest that financial globalization has an adverse impact on the US ecosystem. Specifically, a 1% spike in FGOB reduces LCF by 1.193% in the long run and by 0.502% in the short run. This result is inconsistent with the examination of Akadiri and Adebayo (2021), which shows that, in India, pollution levels grow when financial globalization declines, but they drop when it increases. This inference is supported by findings by Xu et al. (2022) and Akadiri et al. (2022), which found a positive correlation between financial globalization and load capacity factor in Brazil and India, accordingly. Generally speaking, the globalization of finance symbolizes the development of a country's economic sector; a sophisticated financial system would place investments in ecological sustainability ahead of environmentally damaging growth paths (Raihan et al., 2023).

Similarly, there is a negative correlation between LTI and LLCF, with each 1% rise in TI reducing LCF by 0.127% in the long run and 0.00253% in the short run, and this result is significant at the 1% level. Research by Su et al. (2021) concluded that advances in technology raised emission levels in Brazil. The above findings illustrate that the United States has not yet invested in or implemented green technologies to ensure environmental sustainability. Similarly, Adebayo and Kirikkaleli (2021) verified that technological developments worsen Japan's environmental conditions and raise carbon emissions. This result aligns with the conclusions of Lin and Zhu (2019). That said, it goes contrary to the studies conducted by Khan et al. (2020) and Shahbaz et al. (2020), which found that technological innovation enhances the environmental condition.

Table 5. ARDL Long-Run and Short-Run Results

VARIABLES	LR	SR
LGDP	-3.449***(11.5676)	
$LGDP^2$	1.184***(0.52519)	
LPAI	0.015**(0.03079)	
LFGOB	-1.193***(0.2959)	
LTI	-0.127**(0.16542)	
LURBA	1.182(5.1537)	
D.LGDP		-4.242**(4.26804)
$D.LGDP^2$		0.156**(0.19304)
D.LPAI		0.462***(0.00743)
D.LFGOB		-0.502***(0.15540)
D.LTI		-0.00253(0.0074)
LURBA		17.204***(2.34298)
ECT (Speed Adjustment)		-0.684***(0.08539)
Constant		10.910***(31.2434)
R-square	0.8780	

Additionally, the positive and statistically significant URBA coefficients indicate that both long-term and short-term increases in LURBA negatively affect environmental quality. A 1% increase in URBA raises LCF by 1.182% in the long run and by 17.204% in the short run. The finding suggests that the current urbanization structure in the United States is not conducive to reducing pollution. Research conducted in Singapore by Ali et al. (2017), Saudi Arabia by Raggad (2018), and 19 other countries by Saidi and Mbarek (2017) explored that urbanization enhances the quality of the natural world by lowering emissions of carbon dioxide. But, Wang et al. (2016) found that greater urbanization boosts CO_2 emissions. However, our study's outcomes contradict Solarin et al. (2021), who reported that urbanization does not impact the environmental quality of Nigeria.

The DOLS, FMOLS, and CCR techniques are utilized to check the consistency and efficiency of the ARDL results and are presented in Table 6. The economic growth coefficients in the FMOLS, DOLS, and CCR computations are statistically significant at the 1% level and have negative values. It can be concluded from the estimated components that an increase of 1% in GDP causes the LCF to fall by 13.532%, 7.325%, and 14.135%, respectively. The higher R-squared values suggest that the estimation was appropriate. A 1% increase in LPAI leads the LCF to grow by 0.013%, whereas an extra 1% in $LGDP^2$ enables the LCF to expand by 0.625% in the FMOLS model. These figures are noteworthy and corroborate the ARDL conclusion provided before. Additionally, a 1% surge in LURBA raises the LCF by 7.428%, whereas a 1% expansion in LTI encourages the LCF by 0.037%. These outcomes also align with the ARDL short and long-run estimation. Conversely, a 1% spike in LFGOB causes the LCF average to drop by 1.243%. Similar to the ARDL results, the coefficients $LGDP^2$, LPAI, and LFGOB are significant at the 1% level of significance, whereas LTI and LURBA are significant at the 5% level.

Within the DOLS model, an extra 1% in LGDP2, LPAI, LTI, and LURBA raises an average of 0.271%, 0.045%, 0.568%, and 8.671% in LCF. The value of the ARDL results in Table 05 is confirmed by the statistically significant values of these variables. Conversely, a one percent rise in LFGOB leads to an average 1.930% reduction in LCF. Similar to the ARDL conclusions, the coefficient of LFGOB is significant in this particular case. The CCR observations exhibit a similar pattern, except for the LFGOB example. An average of 0.652%, 0.0153%, 0.045%, and 7.796% of LCF are spiked by an additional 1% in LGDP2, LPAI, LTI, and LURBA in the CCR model. Conversely, an extra 1% in LFGOB causes an average 1.236% decrease in LCF.

Table 6. Robustness Check

Variables	FMOLS	DOLS	CCR
LLCF dependent			
LGDP	-13.532***(4.4923)	-7.325**(5.8932)	-14.136***(6.7150)
$LGDP^2$	0.625***(0.2035)	0.271**(0.1827)	0.652***(0.3053)
LPAI	0.013***(0.0121)	0.045**(0.0985)	0.0153**(0.0183)
LFGOB	-1.243***(0.1619)	-1.930***(0.5920)	-1.236***(0.1923)
LTI	0.037**(0.0722)	0.568*(0.4841)	0.045**(0.0950)
LURBA	7.428**(2.2595)	8.671*(3.6591)	7.796***(2.8327)
C	44.608**(18.0927)	27.8901**(16.5672)	46.294**(25.9663)
R-squared	0.9013	0.9641	0.9005

The findings of causal linkages across several economic indicators are presented in Table 7. An F-statistic of 3.38826 and a p-value of 0.0499 indicate that LLGDP does not Granger-cause LLCF. This suggests that we reject the null hypothesis that there is no link between variables at the 5% significance level. Furthermore, p-values below the usual significance threshold confirmed the observation of one-way causation from LGDP2, LPAI, and LTI to LLCF. Therefore, in these circumstances, we reject the null hypothesis that there is no causation. Nonetheless, a strong two-way causal relationship was discovered between LLCF and LGOB, as well as between

LURBA and LLCF. On the other hand, p-values higher than the traditional significance level for each case demonstrated that there was no significant causal relationship between LLCF and LPAI, LLCF and LGDP, LLCF and LGDP, or LLCF and LTI. As a result, the null hypothesis that there is no causation in these interactions is not successfully rejected.

Table 7. Results of Pairwise Granger Causality test

Null Hypothesis	Obs	F-Statistic	Prob.
LGDP $\neq$ LLCF	30	3.38826	0.0499
LLCF $\neq$ LGDP		0.44313	0.647
LGDP2 $\neq$ LLCF	30	3.4843	0.0463
LLCF $\neq$ LGDP2		0.44696	0.6446
LPAI $\neq$ LLCF	30	2.75848	0.0027
LLCF $\neq$ LPAI		0.2652	0.7692
LFGOB $\neq$ LLCF	30	6.05754	0.0072
LLCF $\neq$ LFGOB		0.18985	0.0283
LTI $\neq$ LLCF	30	3.76786	0.0071
LLCF $\neq$ LTI		0.87713	0.4284
LURBA $\neq$ LLCF	30	2.68762	0.0077
LLCF $\neq$ LURBA		5.37891	0.0114

Table 08 displays the diagnostic examination outcomes. The results demonstrated that the usefulness of all diagnostic procedures is insignificant, and the null hypothesis cannot be rejected. According to the p-value of 0.8027, the Jarque-Bera assessment confirms that the residuals appear to be normally distributed. The Lagrange Multiplier analysis shows no serial correlation in the residuals, with a p-value of 0.9463. Lastly, the Breusch-Pagan-Godfrey assessment confirms that the residuals do not exhibit heteroscedasticity, with a p-value of 0.3411.

Table 8. The findings of diagnostic tests

Diagnostic tests	Coefficient	p-value	Decision
Jarque-Bera test	0.43948	0.8027	Residuals are normally distributed
Lagrange Multiplier test	0.05528	0.9463	No serial correlation exits
Breusch-Pagan-Godfrey test	1.1950	0.3411	No heteroscedasticity exists

Conclusion and Policy Recommendation

The present research comprehensively addresses how the LCF in the USA became influenced by private investment in artificial intelligence (AI), economic expansion, financial globalization, technological innovation, and urbanization between 1990 and 2022. The discoveries propose insightful information on the intricate connections between monetary activity and the preservation of the ecosystem. To validate the Load Capacity Curve (LCC) theory, the research makes use of advanced econometric techniques. The findings indicate that while urbanization and PAI reduce the environmental burden, technical advancements, economic growth, and financial integration serve to exacerbate these consequences. The results of the stationarity tests illustrate that the elements in question exhibit a combination of various degrees of integration and do not exhibit unit root problems. The ARDL bound assessment provides further evidence that these factors are cointegrated, indicating the existence of steady long-term linkages. The ARDL calculations demonstrate a favorable association between GDP growth, TI, FGOB, and LCF and provide short- and long-term support for the LCC hypothesis in the USA. This suggests that environmental damage occurs due to economic expansion when insufficient steps are made to safeguard the environment. Conversely, the positive correlations between GDP, TI, FGOB, and LCF convey that these factors might encourage adverse environmental effects. It is anticipated that financial globalization can provide the required funding for investments in eco-friendly technologies and more productive industrial processes. Similar to this, robust and resilient advances in technology, when combined with an openness to trade, might foster the creation of novel concepts and the use of greener practices by stimulating healthy competition and granting access to the latest technologies. The accuracy of the ARDL findings is confirmed by the robustness testing adopting FMOLS, DOLS, and CCR, which increases the credibility of the results. Furthermore, the Pairwise Granger Causality tests exhibit significant one-way causal relationships between LLCF and LGDP2, LPAI, and LTI. These relationships emphasize the relevance of how economic shifts, private investments in artificial intelligence, and improvements in green technology impact the dynamics of ecological sustainability in the USA. Therefore, this investigation suggests several legislative solutions aimed at encouraging sustainable economic development in the United States by leveraging financial globalization, technical improvements, and a feasible urban infrastructure.

In order to tackle the U-shaped correlation discovered in our study between income and environmental sustainability, the United States should adopt a comprehensive and diverse policy strategy. At first, the focus should be on providing green technology and sustainable practices to lower-income areas. This may be done by offering subsidies for the adoption of renewable energy and providing incentives for eco-friendly enterprises. As income levels increase, it is necessary to enhance laws in order to reduce environmental degradation caused by higher levels of consumption and industrial operations. This entails implementing rigorous emissions regulations, advocating for energy conservation, and allocating resources towards sustainable infrastructure. To promote sustainability among high-income groups, policymakers can incentivize investments in clean energy through tax benefits, implement carbon pricing systems, and allocate funds for new environmental technology. Furthermore, it is imperative to strengthen education and awareness initiatives on sustainable behaviors among individuals of all income brackets in order to cultivate a societal ethos of environmental accountability. It is imperative for federal and state governments to cooperate in order to guarantee the efficient implementation of these policies, while also customizing them to suit the specific requirements of each region. Through the implementation of this all-encompassing strategy, the United States may utilize economic expansion to enhance environmental results and attain enduring sustainability.

In order to maximize the beneficial effects of private investment in AI on environmental sustainability, the United States should implement specific and focused regulatory initiatives. Firstly, offers tax incentives and subsidies to private firms that invest in AI technologies that improve environmental sustainability, such as smart grids, precision agriculture, and predictive maintenance to minimize waste and emissions. Facilitate the formation of collaborations between the public and commercial sectors to expedite the implementation of sustainable solutions powered by artificial intelligence. This will ensure that even small and medium-sized firms have the opportunity to benefit from these advancements. Enforce policies that promote openness and accountability in the use of AI technology to mitigate unanticipated adverse environmental effects. Increase research and development funding for artificial intelligence (AI) programs that specifically target sustainability, with an emphasis on promoting innovation in areas such as climate modeling, resource management, and energy efficiency. Furthermore,

advocates for the use of artificial intelligence (AI) in environmental monitoring and enforcement endeavors to enhance adherence and effectiveness. Advocate for workforce development projects that focus on cultivating proficiency in artificial intelligence and environmental sustainability. This will ensure the availability of a highly qualified labor force capable of driving progress in these areas. To leverage technology developments and establish itself as a frontrunner in the green economy, the United States may provide a favorable climate for private investment in AI, therefore promoting significant strides in environmental sustainability.
In order to counteract the negative effects of technical innovation and financial globalization on reducing the LCF, the United States should implement a strategic policy framework. Firstly, policies should be established that promote the use of sustainable technical innovations, with a focus on optimizing resource utilization and reducing environmental impacts. Offer incentives to encourage enterprises to create and use environmentally friendly technologies that increase the ability to handle workloads without using up resources. Facilitate responsible financial globalization by implementing regulations that guarantee investments, uphold sustainable practices, and refrain from exploiting natural or human resources. Enhance global collaboration to harmonize worldwide financial transactions with sustainability objectives, guaranteeing that overseas investments and technology transfers make a positive contribution to environmental sustainability. Promote and fund research and development in sustainable technologies and practices, encouraging innovative solutions that achieve a balance between economic growth and environmental stewardship. In addition, education and training programs that specifically target sustainable practices and the environmental consequences of globalization should be improved, equipping the workforce to participate actively in and promote these endeavors. Through the incorporation of these policies, the United States can effectively tackle the difficulties presented by technical advancement and financial globalization, guaranteeing long-term growth and safeguarding the nation's ability to support future generations.

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