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Enrichment of Environmental Sustainable Development, Green Finance, and Economic Complexity for Reduction of Ecological Footprints

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ABSTRACT

Green finance is anticipated to play a crucial role in balancing environmental sustainability with economic growth, enabling the growth of several industries. Using data from 41 countries between 2004 and 2022 and a Panel Vector Autoregressive (PVAR), the analysis shows that the impact of green finance and CO_2 on economic complexity was positive in the whole period, while the reverse relationships were negative in the whole period. Meanwhile, green finance positively impacts CO_2 in the whole period, and vice versa. This emphasizes the need for stronger, more thoughtfully crafted regulations that strike a balance between sustainability and economic expansion.

Keywords: Economic Complexity, Institutional Quality, Panel Vector Autoregressive, Green Financing, Global Countries
JEL Classifications: F21, G21, O16, C33

1. INTRODUCTION

Substantial setbacks in global sustainable development are highlighted in the most recent United Nations assessment on achieving the sustainable development goals (SDG) in 2023. The SDG Index has experienced a fall in comparison to 2021, which can be partially ascribed to subpar performance in the areas of "SDG-13 on climate action" and "SDG-15 on conserving biodiversity, terrestrial ecological systems, and arresting the degradation of biodiversity." The process of unsustainable economic expansion is one of the leading causes of this problem (Acheampong and Opoku, 2023; Dietz and Adger, 2003; Otero et al., 2020). Large economies heavily depend on natural resources and traditional energy sources to achieve their comprehensive growth goals. Due to this dependence, there is a more significant ecological footprint, faster depletion of natural resources, and environmental deterioration (Chou et al., 2023; Destek and Aslan, 2020; Falcone, 2023; Li et al., 2023; Wang and Azam, 2024; Zafar et al., 2019). Green economic development strategies, on the other hand, may lessen the impact of over-exploitation on natural resources, promoting their recovery and a smaller environmental footprint. However, as the population continues to grow, energy use, particularly from conventional fuels, has become unsustainable, increasing environmental footprints (Zafar et al., 2019; Bekun et al., 2019).

Policy tools are necessary to address these issues and stop the economy's excessive growth. These steps can aid in internalizing the damaging environmental externalities of economic growth. During the COP26 conference, world leaders specifically called on countries to improve their capacity for domestic production by means of structural change and technical innovation (UNFCCC, 2021). The manufacturing process will become more complex as a result of the development of increasingly complex technology and the growth of knowledge, especially in large, complex economies (Ikram et al., 2021; Li, 2024; Shen and Zhang, 2024; Sima et al., 2020). These countries will overcome the previous scale effect by utilizing the method impact of the development procedure on the natural landscape, thanks to the steady progression of technology, skill development, and knowledge base expansion. To achieve structural change, modernization, and technical sophistication—and to meet the objectives of COP21 and COP26 concerning green growth and the reduction of environmental degradation—we must follow the trajectory toward complicated production structures. Understanding the energy challenges related to an increasing population growth rate is crucial, in addition to achieving equitable development through technological developments and supporting the consumption of renewable sources (Fang et al., 2025; Hassan et al., 2024; Mohsin et al., 2022; Yi et al., 2024; Zhao and Shah, 2024). Consequently, earlier research has shown the crucial impact that using renewable energy sources plays in decreasing environmental degradation and biodiversity decline (Balsalobre Lorente et al., 2023; Cui et al., 2023; Destek and Aslan, 2020; Osman et al., 2023). Therefore, having a thorough understanding of how renewable energy fits into the larger picture of population growth is crucial to addressing climate challenges. appropriate rules on energy efficiency and use based on this knowledge.

The benefits of economic complexity (EC) have been highlighted in recent research with regard to money transfers (Patelli et al., 2022; Piras, 2023), finance (Andrew et al., 2024; Ndoya et al., 2023; Nguyen and Su, 2021), business ownership (Ajide, 2022), along with additional economic factors (Zhu and Li, 2017; Lapatinas, 2019). The impact of foreign direct investment (FDI) on EC is one area that has not gotten much study, though. The connection between EC and FDI in developing countries is not well understood, with the exception of studies by Nguea (2024), Ranjbar and Rassekh (2022), Sadeghi et al. (2020), and Saqib and Dincă (2024) that look at how the two variables are causally related. This work fills this void in the body of knowledge. The objective of this research is to investigate how foreign direct investment affects the complexity of the economy in developing nations.

The capacity and structure of the economic system's production are factors that affect its complexity (Phale et al., 2021; Sepehrdoust et al., 2019; Zhang et al., 2022). It incorporates product diversification for export by utilizing domestic expertise to transform inputs into outputs. Antonietti and Franco's (2021) recent study suggests that foreign direct investment (FDI) could be a means of increasing the complexity of the economy. According to the endogenous growth model, Romer's (1993) viewpoint is theoretically related to this idea. The author emphasizes that foreign direct investment is the means by which new ideas and products that need technical know-how to be used effectively in the economy are brought to the domestic market.

In studies of environmental concerns, carbon dioxide is often used as a proxy by researchers because it constitutes the largest percentage of greenhouse gases. However, as only a tiny percentage of the environment is made up of carbon emissions and do not sufficiently account for environmental damage, many academics disagree with this approach. CO_2 emissions, in the opinion of Nathaniel et al. (2021), do not accurately anticipate the stock of readily available resources, including soil, oil, gas, petroleum, and forests. We require a proxy that can fully account for environmental sustainability, giving decision-makers and other authorities a more thorough understanding of the environment when they have access to the right data. Ecological footprint is a commonly recognized measure of environmental quality that may be applied to resource management and assessment (Akyol Özcan, 2024; Alvarado et al., 2021; Genta et al., 2022; Khezri et al., 2023). The ecological footprint serves as a gauge of how quickly resources are being used by humans and garbage is being produced, compared to how quickly nature can absorb it. "The impact of human activities measured in terms of the biologically productive land and water to produce the goods consumed and to assimilate the wastes generated" is what it captures, precisely. It gives an indication of how much natural capital people are willing to pay for. At the individual, regional, and global levels, ecological footprints can be compared. Resources that are renewable are the primary emphasis of ecological footprints (Azimi and Rahman, 2024; Danish et al., 2020; Dogan and Shah, 2022).

This paper has used the structure of the "environmental Kuznets curve (EKC)" (Grossman and Krueger, 1995) to better comprehend the development of explanatory factors at the turning points throughout the course of economic development. The importance of being green in the economy is emphasized in a recent World Bank Report (2021), especially for emerging nations. The Bank suggests innovation and more funding to promote long-term technical investments to achieve this goal. Identifying significant possibilities and variables for climate change mitigation is our goal, as we recognize the necessity of a consistent technical strategy to match a nation's development ambitions with interrelated challenges associated with natural resources and biodiversity for reducing climate difficulties. It is expected that the study's findings will shed light on how nations can order their priorities when it comes to adopting greener economies. Global energy consumption is predicted to increase by 53% by 2035 due to growing energy needs, according to research from the U.S. Energy Information Administration Agency. By 2035, renewable energy will provide for about 15% of the world's energy demands, with fossil fuels still providing most. Furthermore, according to the prediction, 76% of the world's coal usage will come from China alone (EIA, 2011). In order to counteract environmental depletion and lessen ecological imprint, these estimates present a policy conundrum about the direction of EC, knowledge intensification, and the integration of renewable energy usage.

This study considers economic complexity as one of the primary determinants along with knowledge, competency, and progress connected to production (Bahrami et al., 2022; Oumbé et al., 2023; Şanlı et al., 2024; Tabash et al., 2022). Since the economic complexity index (ECI) is a very accurate and dependable indicator of growth, scientists studying the environment and society have given it a lot of attention in the current economic climate (Esmaeili et al., 2021; Martins et al., 2021; Neagu, 2021). Future investment and production are accelerated by ECI, which also broadens and diversifies the production, resulting in higher energy consumption and pollution levels. Contrarily, economic complexity is better suited to preserve the environment since it prioritizes environmental friendly products, machinery, and research and development as well as the employment of cleaner, greener, and renewable technologies (Agrawal et al., 2023; Čábelková et al., 2023; Mealy and Teytelboym, 2020). Higher energy usage is necessary for the production of complicated items. There are other ways to meet this energy demand: Nuclear power, renewable energy, and fossil fuels. The influence of a nation's manufacturing pattern on the environment is evident. Or, to put it another way, a product's level of complexity could potentially have an adverse effect on the environment by causing pollution and using natural resources. Cities and industries have combined to drive remarkable economic growth in the most economically complex countries in recent years. As these nations have transitioned from agrarian to sophisticated industrialized states, their energy consumption has likewise increased. Thus, these nations are thought to be major contributors to GHG emissions, and their ecological footprint will have an impact on the state of the environment globally in the future (El Geneidy et al., 2021). An estimated measure of productive knowledge, the ECI conveys a nation's capacity to manufacture and export sophisticated goods. The capacity of a country to generate and export more complicated or higher value goods is indicated by a higher ECI value. The literature on ecological footprint has so gained a substantial and valuable addition with this study.

The study makes some contributions. First, it looks into how spillover of knowledge about product and production (EC) affect a country's green investments (GF). Surprisingly, previous studies have not thoroughly studied the connection between EC and GF. While a great deal of studies have been done on EC in certain GF—like solar and wind—the majority of those investigations have mostly used theoretical methods. This study also assesses how political collaboration affects the advancement and uptake of energy system security. This study adds significantly in a number of ways. The first part of the study looks at how strong collaboration between public and private institutions may be fostered by political cooperation. This allows the institutions to work together to pursue larger investments in public-private partnerships, which will further energy system security generation. This is a topic that is frequently disregarded in the existing literature. The study also looks at the value of technical breakthroughs and R&D expenditures in power system security. Reaching objectives for sustainable energy system security requires investing in research and development as well as putting advanced green ideas into practice. The study's principal aim is to comprehend how these elements impact the growth of the power system safety sector. Thirdly, the analysis commences by conducting tests for longitudinal correlations and asymmetry employing the panel vector autoregression (PVAR) model)

Section 2 reviews the literature on the variables. Section 3 goes into great detail on the study's methodology, providing a description of the variables and data. Section 4 displays the findings and commentary. Important conclusions, policy implications, and recommendations for further research are summarized in Section 5.

2. LITERATURE REVIEW

The growth of commodities driven by energy consumption and resource exploitation to meet the requirements of an expanding population has resulted in the neglect of the preservation of natural resources and the advancement of a sustainable environment (Huo and Peng, 2023; Qamruzzaman et al., 2024; Zeng et al., 2024). A possible risk of environmental deterioration is the overuse of natural resources. The connection between the environment, economic development, and energy has been the subject of many studies (Adedoyin et al., 2020; Ahmed and Elfaki, 2024; Anwarya, 2022; Borja-Patiño et al., 2024; Xiong and Xu, 2021). The theoretical foundations of technological advancement, environmental modernization, and complexity, however, emphasize the importance of looking at the relationships between natural resources, EC, and environmental footprint in addition to traditional predictors in the context of the Environmental Kuznets Curve (EKC) (Hacıimamoğlu and Cengiz, 2024; Li et al., 2024; Ma et al., 2024; Wang et al., 2024). This study uses the green footprint index as a complete measure of environmental quality, in contrast to previous studies that frequently concentrated on particular ecological indicators. Environmental preservation is a challenge that industries, academics, policymakers, and environmentalists face. The argument that has been going on for the last 10 years has been about figuring out which essential parts of the environment are being negatively impacted by the overuse of natural resources. To tackle climate problems and achieve specific sustainable development goals (SDGs), such as SDG-6 on environmentally friendly water management, SDG-13 on climate action, SDG-14 on marine preservation, and SDG-15 on preserving terrestrial ecosystems, fighting desertification, and halting biodiversity loss, it is imperative that an integrated approach to environmental depletion be taken.

In addition, much research has been done to determine how human activity harms the ecosystem. An increasing amount of literature uses ecological footprints to measure environmental degradation (Hacıimamoğlu and Cengiz, 2024; Li et al., 2024; Ma et al., 2024; Wang et al., 2024). According to Destek and Sinha (2020), the environmental footprint indicator thoroughly assesses the pollution in the air, soil, and water. By considering land areas for agriculture, livestock production, fishing, forests, man-made capital, and the ecosystem's ability to absorb carbon dioxide brought on by human activity, it helps determine the influence of human activity on the environment. Ikram et al. (2021) have demonstrated that the ecological footprint indicator is a valuable instrument for thorough ecological analysis and policy formulation since it enables an assessment of resource consumption limits concerning sustainability concerns. To address environmental challenges, researchers have conducted extensive empirical studies at the regional, national, and panel levels. These studies assess the interplay of demographic, environmental, energy, and economic indices (Rafique et al., 2022). These research shed light on the important factors that affect environmental quality, such as energy, population, and economic concerns.

2.1. The Ecological Footprint and Economic Complexity

In recent years, time series research (Pata et al., 2023; Yilanci and Pata, 2020) and panel studies (Abbasi et al., 2021; Anwar et al., 2024; Rafique et al., 2022, 2022; Tabash et al., 2024) have made extensive use of the economic complexity (EC) indicator to examine its relationship to the environment. Nevertheless, few research works have examined how economic complexity affects ecological footprint metrics. Yilanci and Pata's (2020) study investigates the applicability of the EKC for China between 1965 and 2016. According to the study, the EKC is invalid in China. Moreover, the environmental footprint in China is negatively impacted by EC, as evidenced by the results of the Fourier ARDL technique. The study highlights how crucial it is to use environmentally friendly production techniques to lessen environmental harm. Similarly, Rafique et al. (2022) use rich panel data spanning 38 years to investigate the relationships between environmental footprint and EC for the top 10 nations with the highest EC. The results show that the ecological footprint is significantly increased by economic complexity and urbanization and that it is decreased by the use of renewable energy.

Nguyen and Doytc (2022) investigated 95 nations classified by income levels worldwide, exposing varied impacts of EC on environmental footprints within different nation clusters. Across the board, their results showed a clear "inverted U-shaped" association between ecological footprint and EC. Akadiri et al. (2022) conducted a new study that utilized quarterly datasets from 1985 Q1 to 2019 Q1 to examine China. The study demonstrated the positive influence of EC on environmental footprint. Moreover, nonparametric causality analysis showed that the impact varied amongst quantiles. Otherwise, renewable energy sources benefit the environment. The study's conclusion recommends that policymakers support the use of sustainable energy sources to reduce environmental concerns and promote green growth.

The impact of EC on Japan's environmental footprint has been studied by Wang et al. (2023a; 2023b). They used a nonlinear ARDL model to analyze data from 1990 to 2020 and found both symmetric and asymmetric effects. The results showed that while an adverse shock would have a negative impact on environmental quality, a beneficial surprise to economic complexity might reduce the nation's ecological footprint. A second investigation by Saqib et al. (2023) investigated the possible connection between G-10 countries' carbon emissions and economic complexity. Their findings suggested that economic complexity has a negative short- and long-term impact on carbon emissions. Furthermore, Alola et al. (2023) investigated the factors contributing to ecological deterioration in some Nordic nations. They distinguished between complexity outlook and economic complexity and looked at the effects of these differences on greenhouse gas emissions. Using a random effect model and data spanning from 1995 to 2020, the scientists discovered that whereas economic complexity outlook stimulated GHG emissions, it also attenuated them.

Considering the previous conversation, the correlation between financial complexity and ecological impact indicator produces a variety of results, indicating a confusing situation that is consistent with the claim put out by Hidalgo and Hausmann (2009). The 50 most complicated economies—which actively work to increase production complexity and structural advancement—have not received enough attention in the literature yet. Moreover, we investigate the indirect effect of EC via economic development, a topic not fully covered in previous studies. As a result, the current research looks into how the 50 most complicated nations are affected by economic complexity. Drawing on the knowledge acquired from the previously described study, the first theory of this investigation might be articulated as follows:

H_1: Ecological footprint can be positively or negatively impacted by economic complexity.

2.2. Green Finance and Ecological Footprint

Energy transition theory provides the foundation for the nexus between renewable or clean energy and ecological quality. According to this hypothesis, switching from fossil fuels to renewable energy is essential to improving ecological quality through decreasing releases (Chen et al., 2023; Jaiswal et al., 2022; Yang et al., 2024).

Energy utilization closely related to the direction of economic expansion, and energy use may impact the state of the environment. In theory, aiming for growth goals could increase the need for energy, and if that energy is obtained by extracting fossil fuels, it could worsen the environment and increase ecological footprints. Otherwise, utilizing renewable energy contributes to reducing the amount of conventional energy sources extracted, which significantly lessens the ecological footprint. Scholarly works (Danish and Senjyu, 2023; Ma et al., 2024; Xue et al., 2022) have examined the connection between ecological footprint. Danish and Khan (2020) discovered that using renewable energy has a positive environmental footprint for the BRICS nations, supporting the Environmental Kuznets Curve (EKC) for these nations. Similarly, even though the EKC has not been proven in these circumstances, Sharma et al. (2021) showed that adopting renewables reduces the ecological footprint in underdeveloped countries. According to Zhang et al. (2022), the production of energy from nuclear and wind sources lessens their ecological imprint; however, the production of power from hydro and geothermal sources may harm the ecosystem. Their analysis also showed how research and development (R&D) expenditures could improve environmental quality. Recent research has shown inconsistent proof that renewable energy can have a beneficial or detrimental impact on environmental harm as assessed by emissions and carbon footprint. Using quantile-based estimation, Yang et al. (2022) discovered that sustainble energy can reduce negative effects in the lower and upper quantiles but not in the medium quantiles. Furthermore, using region-based research, Zaman et al. (2016) investigated the environmental effects of biofuel production and found a positive correlation between biofuel production and climate change throughout the panel.

A well-known idea in theoretical literature, the resource curse theory suggests that having a large quantity of natural resources could be a recipe for economic disaster. According to classical economics, natural resources could boost economic growth, prevalent before the 1950s. But after World War II, it was clear that developing nations with fewer natural resources frequently did better than those with an abundance of them. According to recent research, nations that rely less on natural resources typically have lower carbon intensities. Several scenarios have been used to test this notion (Danish and Senjyu, 2023). However, there needs to be more agreement in the scientific research regarding how natural resources affect the environmental footprint indicator. A number of research, including those by Majeed et al. (2021), Adebayo et al. (2022a; 2022b), and Zafar et al. (2019), show a positive correlation between the ecological footprint and natural resources. On the other hand, research by Destek and Sinha (2020) indicates that natural resources and ecological footprint are negatively correlated. There are some potential explanations for the varied empirical results, including changes in institutional quality, economic development levels, environmental legislation, and commercial obligations about exploiting natural resources. Geographical regions can also be blamed for differences in how natural resources are used and how this affects ecological footprints. Moreover, these discrepancies are partly because industrialized and developing nations have different environmental legislation (Kırda and Aytekin, 2024; Zhang et al., 2024).

The aforementioned conversations have, for the most part, focused on the favorable correlation between renewable energy usage and environmental footprint. Therefore, the following is a formalization of the third thesis of this study:

H_2: The ecological footprint is adversely impacted by green financing.

2.3. The Current Study's Novelty and Research Gap

To understand the factors contributing to ecological degradation, the literature that has already been written about the impact on the environment has put forth and tested several hypotheses. Numerous aspects, such as population, economic growth, natural resources, disaggregated energy use, and economic complexity, have been examined in these research. Some have looked at the consequences of these factors separately, while others have looked at their combined effects in several different nations. There are notably few studies in the literature that look at how the EKC framework's consideration of natural resources, population density, EC, and renewable energy affects the environmental footprint. By analyzing the ecological impact in 50 significant complex economies, this study uniquely contributes to understanding how various factors can increase or decrease environmental deterioration. The knowledge acquired can help policymakers target particular issues that have a significant impact on their countries' ecological conditions to address Sustainable Development Goal 13 (Climate change).

The current study examines how economic complexity affects the environmental footprint within the context of the EKC, taking into account the effects of resource extraction, the usage of renewable energy, and population pressure. Our study emphasizes the dearth of such studies in the literature by utilizing robust econometric methodologies to remove potential biases, such as heteroskedasticity and cross-sectional dependence (CSD). Therefore, by employing sophisticated empirical approaches, our contribution advances the current scholarly discourse on the drivers of the environment's quality.

3. DATA AND EMPIRICAL METHODOLOGY

3.1. Descriptions of Statistics and Matrix of Correlation

Panel A of Table 1 indicates the descriptive statistics for the variables analyzed, including green finance (*GF*), economic complexity index (*ECI*), and CO_2 emission (*CO2*). The sample consists of countries from 2004 to 2021. The mean green finance is 1.26, with a standard deviation of 2.18, ranging from −2.66 to 9.04. The Economic Complexity Index has a mean score of 0.93 with a standard deviation of 0.82, ranging from −2.7 to 2.76. The mean score of CO_2 emissions is 4.61, with a standard deviation of 1.4, ranging from 1.86 to 8.69.

Panel B of Table 1 displays the correlation matrix for the items we examined in our analysis. If the correlation coefficient among the dependent factors is more than 0.7, multicollinearity can be a problem. The matrix, however, shows no such problem because the coefficients for green finance, economic complexity index, and CO_2 emission all stay below 0.7.

We analyze variable stationarity using the latest panel unit root tests. We apply Im, Pesaran and Shin (IPS) tests for the unit root of the panel nations.

Using the most recent panel unit root tests, we examine variable stationarity. The common unit root is the Levin, Lin, and Chu (LLC) and Im, Pesaran, and Shin (IPS) tests (Levin et al., 2002). We also used the CIPS technique, which takes into consideration any heterogeneity among the panel nations as well as cross-sectional dependency.

Table 2 illustrates stationarity tests of our variables using single-constant processes. Economic complexity is stationary and statistically significant in all tests, and green finance is stationary

Table 1: Summary and correlations

Panel A: Descriptive statistics								
Variable	**Definition**	**Measure**	**Source**	**Obs**	**Mean**	**SD**	**Min**	**Max**
GF	Green finance	Green energy debt flows	IRENA	738	1.263123	2.182053	−2.65951	9.038243
ECI	Economic complexity index	The number and complexity of the products	Harvard growth lab	738	0.93051	0.827569	−2.69588	2.756136
CO_2	CO_2 emissions	Total CO_2 emissions	WDI	738	4.616858	1.404297	1.861323	8.691257

Panel B: Matrix of correlations			
Variables	**ECI**	**lnGF**	**lnCO_2**
ECI	1		
lnGF	0.0364	1	
lnCO_2	0.1574	0.1652	1

Table 2: Results of unit root tests

Variables	LLC	IPS	CIPS
ECI	−6.3948***	−5.0384***	−2.144**
lnGF	−5.447***		−2.885***
$lnCO_2$	−1.7316*	1.3964	−1.723

Table 3: Slope homogeneity results

Model	Value	P-value
Model 1Δ	9.906	0.000
Δ adj	11.232	0.000

except in IPS test, while CO_2 only stationary and statistically significant in LLC test.

To investigate cross-sectional slope homogeneity, we used the Pesaran and Yamagata (2008) approach in our investigation. The findings, displayed in Table 3, confirm that the slope coefficients are not uniform.

3.2. Empirical Framework

3.2.1. Panel VAR

A homogeneous panel VAR of order p with k variables and panel-specific fixed effects is represented by the set of linear equations below:

$$Y_{it} = Y_{it-1} A_1 + Y_{it-2} A_2 + +Y_{it-p} A + Y_{it-p} A_p + X_{it} B + u_i + e_{it} \quad (1)$$

$i \in \{1,2.,N\}$, $t \in \{1,2.,T_i\}$

Here, X_{it} represents a $(1 \times l)$ vector of exogenous covariates, Y_{it} denotes a $(1 \times k)$ vector of dependent variables, and u_i and e_{it} are $(1 \times k)$ vectors representing dependent variable-specific panel fixed effects and idiosyncratic errors, respectively. The parameters to be estimated include the $(k \times k)$ matrices $A_1, A_2,...$, and the $(1{\times}k)$ matrix B. It is assumed that the innovations exhibit the following properties for all t > s: $E(e_{it}) = 0$, $E\left(e'_{it}e_{it}\right) = \Sigma$, and $E\left(e'_{it}e_{is}\right) = 0$.

We make the same assumptions as Holtz-Eakin et al. (1988) for the cross-sectional units: that they all have the same reduced-form parameters, $A_1, A_2,...,A_{p-1}$, A_p, and B. Panel-specific fixed effects provide the basis of a systematic cross-sectional heterogeneity model. This configuration is different from random-coefficient panel VAR, where the settings are identified as an approximation of the unit under investigation, or time-series VAR, where the parameters are described as a distribution.[1]

It is possible to compute the fixed effects alongside the previously specified parameters, or alternatively, to eliminate the fixed effects following some variable adjustment and estimate the parameters using ordinary least squares (OLS). Even with a high N, estimations would be biased due to the lagged dependent variables on the right side of the system of equations (Nickell, 1981). Even at $T = 30$, Judson and Owen (1999) simulations demonstrate a large bias, even though the bias goes to zero as T grows.

1 For an overview of panel VAR models with random coefficients, consider Canova & Ciccarelli (2013).

3.2.2. GMM estimation

Numerous estimators using GMM have been created to yield reliable findings in circumstances with fixed T and big N. Regarding Anderson and Hsiao (1982), lagged differences and levels of Y_{it} from previous periods can be used as instruments to reliably estimate the first-difference (FD) model, assuming errors are serially uncorrelated. But there are problems with this strategy. Unbalanced panels may have gaps that are made worse by the FD transformation. For instance, FDs at times t and t–1 are also absent if Y_{it-1} is lacking. Additionally, the required time intervals for each panel rise in tandem with the panel VAR's delayed order. Instruments in levels require at least five observations per subject for a second-order panel VAR.

Forward orthogonal deviation (FOD), which does not share the flaws of the FD modification, was suggested by Arellano and Bover (1995) as a substitute. To reduce data loss, it subtracts from the mean of all accessible future findings rather than employing deviations from past realizations. Since past realizations are not part of the present transformation, they remain valuable tools. That estimation might only account for the most recent observation. For example, when the instruments in a second-order panel VAR are in levels, only $T_i \geq 4$ realizations are required.

An extended array of delays can be used as instruments to increase effectiveness. This method can, however, result in fewer observations, especially in panels that are imbalanced or have missing data. In order to solve this, Holtz-Eakin et al. (1988) proposed building instruments using the available data, supposing that these instruments are uncorrelated with the mistakes and that missing values should be replaced with zero. However, overfitting might happen, particularly when the temporal dimension is tiny, and make the GMM results look like OLS estimates. Reporting the number of instruments and evaluating the resilience of the outcomes to their reduction is advised by Roodman (2009). This problem is less important in big N and large T conditions since the OLS's Nickell bias decreases with increasing T (Alvarez and Arellano, 2003).

Arellano and Bond (1991) developed algorithms for "small T, large N" panels, or many cross-sectional units viewed for brief periods of time. However, simulations by Judson and Owen (1999) demonstrate that the Arellano-Bond and Anderson-Hsiao estimate methods both continue to work well as the time dimension increases. Alvarez and Arellano (2003) demonstrate that the GMM estimators according to orthogonal deviations remain constant in N as the ratio of T/N approaches a positive value of no more than 2 as both N and T approach infinity.

Unit root tests are frequently used in time-series VARs to confirm each variable's stationarity. GMM estimation for linear dynamic panel models is likewise covered by this. Blundell and Bond (1998) state that when the variable being represented is near a unit root, particularly when a unit root occurs, the GMM estimators encounter the issue of weak instruments.

The immediate conditions are completely useless when there is a unit root. Similar to time-series VAR, this problem can be lessened by pretransforming the factors by growth rates or differencing.

Fitting the formulas as a mathematical arrangement may improve efficiency even though equation-by-equation GMM estimation produces reliable estimates of panel VAR (Holtz-Eakin et al., 1988). Assume that the common set of $L \geq kp + l$ instruments is represented by the row vector Z_{it}, where $X_{it} \in Z_{it}$., A number in superscript serves as an index for equations. Examine the modified panel VAR model that follows, which is based on (1) but is presented in a more condensed format:

$$Y_{it} = \overline{Y}_{it}^{*} A + e_{it}^{*}$$

$$Y_{it}^{*} = \left[y_{it}^{1*} y_{it}^{2*} \ldots y_{it}^{k-1*} y_{it}^{k*} \right]$$

$$\overline{Y_{it}^{*}} = \left[Y_{it-1}^{*} Y_{it-2}^{*} \ldots Y_{it-p+1}^{*} Y_{it-p} X_{it}^{*} \right]$$

$$e_{it} = \left[e_{it}^{1*} e_{it}^{2*} \ldots e_{it}^{k-1*} e_{it}^{k*} \right]$$

$$A' = \left[A_1' A_2' \ldots A_{p-1}' A_p' B' \right]$$

Where some alteration of the original variable is indicated by the asterisk. The forward orthogonal deviation is given by $m_{it}^{*} = m_{it} - m_{it-1}$, if the original variable is denoted as m_{it}. T_{it} represents the total number of approaching observations that are available for panel i at time t, and the average of all approaching observations that are accessible is displayed by $\overline{m_{it}}$, $m_{it}^{*} = \left(m_{it} - \overline{m_{it}} \right) \sqrt{T_{it}} / \left(T_{it} + 1 \right)$.

Let us assume that perceptions are continuously layered on panels. For GMM, an estimate is given below

$$A = \left(\overline{Y^{*}} Z \hat{W} Z' \overline{Y^{*}} \right)^{-1} \left(\overline{Y^{*}} Z \hat{W} Z' Y^{*} \right)' \tag{2}$$

Where $\hat{W}$ is an assumed positive semidefinite, symmetric, nonsingular weighting matrix ($L \times L$). If E(Z'e) = 0 and rank $E\left(\overline{Y_{it}^{*}} Z \right)' = kp + l$, then the GMM estimator is consistent. Hansen (1982) states that the weighting matrix $\hat{W}$ could be chosen to attain optimal efficiency.

Cross-equation hypothesis testing is made easier by the joint estimation of the system of equations. The GMM estimate of A and its corresponding covariance matrix can be used to perform Wald tests on the parameters. The premise that all coefficients for the lag of variable m in the equation for variable n are concurrently zero can also be used to assess Granger causality.

3.2.3. Model selection

When performing panel VAR analysis, figuring out the ideal moment circumstances and lag sequence for panel VAR models is essential. Andrews and Lu (2001) developed the model selection criterion for GMM models using Hansen's (1982) J statistic for overidentifying restrictions. The Akaike information criterion (AIC) and other well-known maximum likelihood-based model selection methods are comparable to them (Akaike, 1969). When the GMM estimator in equation (2) is applied to their MMSC, the vector pair (p,q) that minimizes the criteria is selected using the criteria of Andrews and Lu (2001).

$$MMSC_{BIC,n}(k,p,q) = J_n\left(k^2 p, k^2 q\right) - \left(|q| - |p|\right) k^2 \ln n$$

$$MMSC_{AIC,n}(k,p,q) = J_n\left(k^2 p, k^2 q\right) - 2k^2\left(|q| - |p|\right)$$

$$MMSC_{HQIC,n}(p,q) = J_n\left(k^2 p, k^2 q\right) - Rk^2\left(|q| - |p|\right)$$

$$\ln n \; R > 2$$

In this case, $J_n(k,p,q)$ stands for the J statistic for overidentifying limitations in a k-variate panel VAR model of order p, where the sample size is n and the moment conditions are obtained from the q lags of the dependent variables. Only when q>p are the MMSCs listed above applicable. Even for newly identified GMM models, the overall coefficient of determination (or CD) can be calculated as a stand-in statistic. Let Ψ represent the dependent variables' unconstrained ($k \times k$) covariance matrix. The (CD), which is computed as follows, represents the percentage of variation that the panel VAR model can account for:

$$CD = 1 - \frac{\det(\Sigma)}{\det(\Psi)}$$

3.2.4. Impulse-response

We focus on the autoregressive structure of the panel VAR, as stated in equation (1), and eliminate the exogenous variables to simplify our nomenclature. Hamilton (1994) and Lütkepohl (2005) state that a VAR model is stable if all of the companion matrix ‾A's eigenvalues have absolute values that are strictly less than one. The following describes how the companion matrix is constructed:

$$\overline{A} = RejectReject_{0_k}^{0_k}\left[^{I_k}\; A_1 O_k A_2\, 0_k\, I_k A_p\, 0_k 0_k\, I_k A_{p-1}\, 0_k^k 00_k\right.$$

In this instance, stability allows for the definition and inversion of the panel VAR model as the process of an infinite-order vector moving-average (VMA). This feature facilitates comprehension of the estimated forecast-error variance decompositions (FEVDs) and impulse-response functions (IRFs). Converting the model into an infinite VMA, where Φ_i stands for the VMA parameters, allows one to compute the fundamental IRF, represented by Φ_i.

Table 4: PVAR setup of lag

lag	CD	J	J P-value	MBIC	MAIC	MQIC
1	0.9999549	35.19615	0.1339665	−134.3239	−18.80385	−64.00912
2	0.9999534	19.06804	0.3876447	−93.94534	−16.93196	−47.0688
3	0.9999549	9.745353	0.371491	−46.76134	−8.254647	−23.32307
4	0.999952	.	.	.	.	.

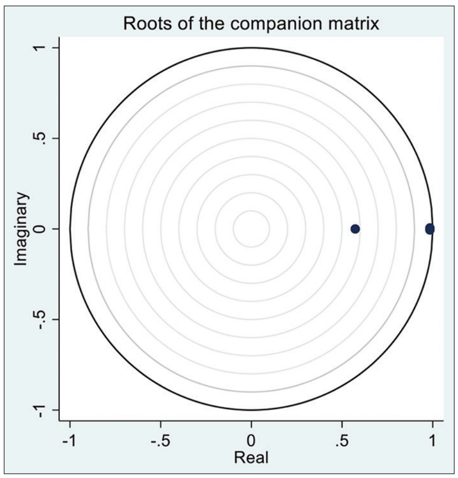
$$\Phi_i = \begin{cases} I_k & i = 0 \\ \sum_{j=1}^{i} \Phi_{t-j} A_j & i = 1, 2, ... \end{cases}$$

Nevertheless, because of the contemporaneous coupling of innovations in fundamental impulse-response functions (IRFs), it is probable that shocks to one variable will also cause shocks to other variables., meaning that IRFs lack a causal interpretation. To solve this, we may create a set ò numbers P in which P' P = Σ. After that, the innovations are orthogonalized using the matrix P by converting them into e_{it} P^{-1}, which then converts the VMA parameters into orthogonalized impulse responses $P\Phi_i$. The system of dynamic equations is essentially subject to identification limits as a result of this approach. Sims (1980) proposed imposing a recursive structure on a VAR model by means of the Cholesky decomposition of Σ. Nevertheless, this breakdown is not exclusive and relies on the arrangement of variables in Σ.

Table 5: Eigenvalue stability requirement

Variables	Eigenvalue		Modulus
	Real	Imaginary	
ECI	0.984303	0.0055826	0.9843188
lnGF	0.984303	−0.0055826	0.9843188
$lnCO_2$	0.572683	0	0.5726831

Figure 1: The unit circle contains a graph of the eigenvalue



The asymptotic distribution of the panel VAR parameters and the cross-equation error variance-covariance matrix can be used to analytically compute intervals of confidence for impulse response functions (IRFs). Alternatively, bootstrap resampling or Monte Carlo simulation can be used to approximate these intervals.

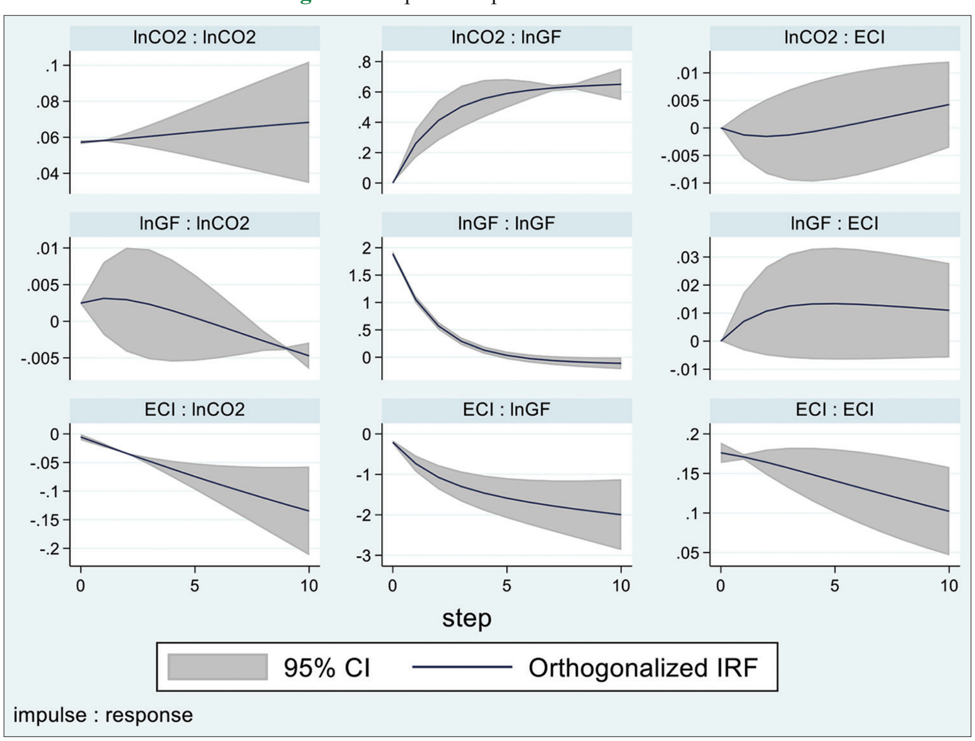
3.2.5. FEVD

For the next h-step, the forecast inaccuracy can be written as

$$Y_{it+h} - E\left(Y_{it+h}\right) = \sum_{i=0}^{h-1} e_{i(t+h-i)} \Phi_i$$

Where Y_{it+h} is the observed vector at time $t + h$ and $E\left(Y_{it_h}\right)$ is the h□step ahead forecast vector generated at time t. Following the shocks' orthogonalization, we compute each variable's contribution to the forecast-error variance using the matrix P, just like in IRFs. The forecast-error variance is easily decomposable due to the covariance matrix I_k of the orthogonalized shocks $e_{it}P^{-1}$. More precisely, the following formula can be used to calculate variable m's impact on variable n's h□step forward forecast□error variance:

Figure 2: Impulse-response function charts



$$\sum_{i=0}^{h-1}\theta_{mn}^{2}=\sum_{i=1}^{h-1}\left(\mathrm{i}_{n}^{'}\mathrm{P}\Phi_{i}^{'}\mathrm{i}_{m}\right)^{2}$$

This denotes the sth column of I_k as i_s. In practice, the contributions are frequently standardized in relation to the variable n's h-step forward forecast-error variance,

$$\sum_{i=0}^{h-1}\theta_{n}^{2}=\sum_{i=1}^{h-1}\mathrm{i}_{n}^{'}\Phi_{i}^{'}\Sigma\Phi_{i}\mathrm{i}_{n}$$

Confidence intervals, like IRFs, can be calculated analytically or by a range of resampling methods.

4. EMPIRICAL FRAMEWORK AND MAIN FINDINGS

4.1. Empirical Framework

4.1.1. Prior tests: Panel VAR setup of lag

The ideal choice of lag order affects the panel VAR model estimate's accuracy. As a result, the panel VAR specification needs to specify the lag order p exactly. The information criteria we employ in our study include the Hannan-Quinn information criteria (HQIC), the Akaike information criteria (AIC), and the bayesian information criteria (BIC). Given that it has the lowest MAIC, MBIC, and MQIC, the first-order panel VAR is the suggested model in Table 4.

4.1.2. Prior tests: The panel VAR model's stability

For a panel VAR to satisfy stability requirements, it must be invertible and exhibit an infinite-order vector moving average, as noted by Abrigo and Love (2016). Stability is typically assessed by examining the magnitude of the eigenvalues calculated for the model. Sigmund & Ferstl (2021) states that if the modulus of each companion matrix eigenvalue is strictly smaller than one, the panel VAR model is considered stable. The computed panel VAR models satisfy the stability requirements, as shown by the results table and eigenvalue diagram. Table 5 lists the eigenvalues whose moduli are rigorously smaller than one. As seen in Figure 1, these eigenvalues lie firmly inside the unit circle.

4.2. Key Findings

4.2.1. The impulse response function (IRF)

With a confidence interval of 95%, Figure 2 shows how green finance reacted to shocks related to economic complexity. We calculate the indicator's responses over a 10-year period to enhance analysis.

While the inverse correlations were unfavorable over the entire period, green finance and CO_2 had a positive impact on economic complexity. Meanwhile, green finance positively impacts CO_2 in the whole period, and vice versa.

4.2.2. The outcomes of the forecast error variance decomposition (FEVD)

Using the Cholesky decomposition of the residual covariance matrix, we computed the forecast error variance decompositions (FEVDs) and impulse response functions (IRFs) in our panel VAR models. FEVDs quantify how much a shock to a particular endogenous variable affects the forecast error variance of each variable. FEVDs describe how each variable contributes to the forecast error variance, in contrast to IRFs, which assess how dependent variables react to shocks. The FEVDs for six panels during a 10-year period are shown in Table 6.

In panel A, economic complexity is self-determined mainly in the short term, with approximately 99.91% of its variation explained by internal dynamics. In the long term, the influence of economic complexity dropped to 99.38%, while the effects of green finance and CO_2 emissions changed insignificantly to 0.6%, and 0.013%.

Table 6: Forecast-error variance decomposition

Panel A. ECI			
Horizon	ECI	lnGF	$lnCO_2$
0	0	0	0
1	0.0093568	0.0018542	0.988789
2	0.0589284	0.0022368	0.9388348
3	0.1324888	0.0020877	0.8654234
4	0.2163453	0.001693	0.7819618
5	0.3000126	0.001271	0.6987165
6	0.3774408	0.0009302	0.621629
7	0.4460842	0.0007025	0.5532133
8	0.5055218	0.0005814	0.4938968
9	0.5563885	0.0005469	0.4430646
10	0.5997267	0.0005769	0.3996964
Panel B. lnGF			
Horizon	ECI	lnGF	$lnCO_2$
0	0	0	0
1	0.0117364	0.9882636	0
2	0.1091551	0.8780894	0.0127555
3	0.2482282	0.717585	0.0341868
4	0.3800003	0.5654318	0.0545679
5	0.4848756	0.4452576	0.0698668
6	0.563647	0.35618	0.080173
7	0.6225575	0.2907191	0.0867234
8	0.6673599	0.2419607	0.0906794
9	0.7022243	0.2048889	0.0928869
10	0.7299864	0.1760942	0.0939194
Panel C. lnCO2			
Horizon	ECI	lnGF	$lnCO_2$
0	0	0	0
1	0.0093568	0.0018542	0.988789
2	0.0589284	0.0022368	0.9388348
3	0.1324888	0.0020877	0.8654234
4	0.2163453	0.001693	0.7819618
5	0.3000126	0.001271	0.6987165
6	0.3774408	0.0009302	0.621629
7	0.4460842	0.0007025	0.5532133
8	0.5055218	0.0005814	0.4938968
9	0.5563885	0.0005469	0.4430646
10	0.5997267	0.0005769	0.3996964

Table 7: Granger causality tests

Hypothesis	
lnGF⇏ECI	1.229
$lnCO_2$⇏ECI	0.066
ECI⇏lnGF	3.958*
$lnCO_2$⇏lnGF	10.320*
ECI⇏$lnCO_2$	3.137
lnGF⇏$lnCO_2$	0.039

In panel B, regarding the response of green finance to others, the same trend was observed in panel A. Green finance is largely self-determined, with over 98.82% of its variation explained by its internal dynamics. At the same time, economic complexity exerts a minor influence, accounting for 1.17% of the variation in the short term.

In panel C, the response of CO_2 emission is over 98.87%, explained by its internal dynamics in the short term. At the same time, economic complexity and green finance exert minor influences, accounting for 0.94% and 0.19% of the variation in the short run. However, the response of CO_2 emission to its shocks declined to 39.96% in the long run while the impacts of economic complexity became more prominent at 59.97%, and that of green finance is 0.57%.

4.2.3. Granger causality results

Granger causality tests identify the dynamic transmission mechanism of green finance and economic complexity.

According to Table 7's Granger causality results from PVAR (1), significant interactions among economic complexity, green finance, and CO_2 emissions are revealed, with economic complexity and CO_2 emission cause significant changes to green finance.

5. CONCLUSION

This study highlights the critical role of frequent public expenditure in promoting inclusive growth in Vietnam. Using data from 41 countries between 2003 and 2021 and a panel vector autoregressive (PVAR), the analysis shows that the effest of green finance and CO_2 on economic complexity was positive in the whole period, while the reverse relationships were negative in the whole period. Meanwhile, green finance positively impacts CO_2 in the whole period, and vice versa. This emphasizes the need for stronger, more thoughtfully crafted regulations that strike a balance between sustainability and economic expansion.

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