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Statistical Methods Estimate Interactions Between Environmental, Social Governance, and Foreign Direct Investment

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Abstract: This study examines the relationship between environmental, social, and governance (ESG) performance and flows of foreign direct investment (FDI). Sustainability and climate change are becoming more prominent regulatory priorities, which is why this research is important. This article zeroes in on the correlation between ESG (environmental, social, and governance) performance and FDI (foreign direct investment). This study looks at EU states from 2017 to 2025 to see whether FDI draws higher ESG performance and if FDI inflows lead to changes in ESG principles. This research spans the years 2017 through 2025. In order to shed light on complex nonlinear relationships, we use a two-pronged approach: first, we use fixed-effects panel regressions to analyze the impact of environmental, social, and governance (ESG), carbon intensity, and business conditions on foreign direct investment (FDI), taking into consideration the impact of interest rates; second, we use a multilayer perceptron (MLP) model to shed light on these relationships. There are a number of metrics that are used in order to assess the efficiency of the model. Some of these measurements are MAE, RMSE, and R^2. The figure that represents the R-squared value illustrates the value that has been established. The objective of this project is to give thorough information on the link between ESG (environmental, social, and governance) aspects and foreign direct investment (FDI). This will be accomplished via the use of both traditional econometrics and machine learning methodologies. In addition, our research provides policymakers with suggestions that may be implemented if they so choose. This gives them the ability to construct incentives that are founded on facts and that promote both economic gain and sustainable development.
Keywords: Machine Learning Models, panel regression techniques, environmental governance, green financial markets, foreign direct investment flows.

1 Introduction

When seeking to attract foreign direct investment (FDI), an essential source of capital for both developed and developing countries to support social and economic progress, environmental, social, and governance (ESG) considerations are increasingly taken into account. Investors' decisions are often influenced by their assessment of a country's ESG performance [1].

Despite the growing importance of sustainability in investment decisions, there has been limited quantitative research examining how ESG performance affects FDI inflows, particularly within the European Union (EU).

This study investigates the relationship between FDI inflows to EU member states and ESG performance over the period 2017–2025. The research integrates observable indicators to illustrate how sustainability influences economic, social, and environmental outcomes. Social performance is proxied by the labor conditions index, environmental performance by carbon intensity, and interest rates are included as a control variable. The objective is to provide a

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comprehensive analysis of how countries with strong ESG performance might attract foreign investment through targeted policies.

To carry out a thorough examination, the study employs a dual analytical framework. First, a fixed-effects panel regression model is used to assess the impact of ESG performance on FDI, accounting for both observable and unobservable differences across countries, as well as changes over time. This method allows for clear identification of variable relationships and ensures robust and reliable statistical results. Second, multilayer perceptron (MLP) neural networks are applied to capture complex nonlinear relationships that traditional regression techniques may not adequately describe. By combining traditional econometric methods with advanced machine learning approaches, the analysis achieves more accurate and insightful results regarding the influence of ESG factors on FDI.

The paper is organized into six main sections. The first section introduces the study and its motivations. The second reviews the existing literature on ESG and FDI. The third section details the fixed-effects panel model, followed by the fourth section, which presents the MLP neural network methodology. The fifth section discusses and analyzes the findings, and the sixth section concludes with policy implications and suggestions for future research. The study aims to provide policymakers and stakeholders with evidence-based insights and methodological guidance to leverage sustainability performance in attracting foreign investment, using a combination of rigorous statistical analysis and advanced predictive modeling techniques.

2 literature review

Global movements toward sustainable development and the green economy have led to an increase in research on the influence of non-financial factors on overseas investment decisions. Several studies have shown that, in addition to traditional economic indicators, global investors consider sustainability, governance transparency, and the implications of social and environmental performance for long-term risk when evaluating potential investment locations [2]. Research by [3] found that environmental, social, and corporate governance (ESG) rules significantly influence investment patterns. Similarly, [4], distinguishes between eco-innovation and conventional innovation, highlighting the importance of innovation in enhancing corporate market value. While conventional innovation may increase corporate value, it often generates carbon emissions with negative environmental consequences. In contrast, investments in eco-innovation benefit both profitability and the environment.

The study conducted by [5]. examines how changes in ESG ratings affect the efficiency of capital market pricing, using data from Chinese A-listed companies between 2010 and 2023. The results indicate a significant inverse correlation: higher ESG rating changes lead to increased asset mispricing, reducing market pricing efficiency. The research presented in [6] offers a framework for integrating sustainable investing principles to achieve long-term growth. Further, [7] provides an overview of approaches, benefits, and global trends, including the Environmental Sustainability Index (ESI), the Sustainable Development Fund, the ESG Index, and voluntary corporate social responsibility disclosures in India. Findings suggest that countries with strong governance attract more FDI, whereas those with high Human Development Index scores may attract less. High FDI inflows are also associated with increased carbon emissions in emerging economies, and sustainability reporting appears to attract investment in commodity-exporting nations.

To better understand the role of ESG regulations and policies in attracting FDI [8]] contributes to the knowledge of how these rules influence investment. Building on previous research on ESG practices and FDI, [9] emphasizes foreign investment through local equity markets. Similarly, [10] provides quantitative data on the impact of ESG performance on the international operations of Chinese A-listed firms from 2009 to 2020, taking into account the extent of cross-border operations [11] Research by [12]. explores the relationship between sovereign ESG indicators and FDI in Gulf Cooperation Council (GCC) states from 2000 to 2022, highlighting the limited research on climate change impacts at the firm level. Evidence shows that FDI, particularly in technology and renewable energy sectors, demonstrates resilience. Important factors include macroeconomic stability, regulatory frameworks, high-quality infrastructure, and supportive government policies such as tax incentives and expedited procedures [13] Additional studies [14] emphasize the growing significance of environmental openness, technological innovation, and regulatory incentives for advancing FDI flows. ESG concepts, covering environmental, social, and governance dimensions, are increasingly important across financial markets, corporate governance, trade, investment, business practices, and national legislation [15] [16] These studies also employ methodologies such as big data analytics and instrumental variable techniques to address endogeneity in ESG investments. Finally, [17] and [18] provide historical and theoretical perspectives on FDI, covering classical and neoclassical frameworks and extending to contemporary concepts such as multinational corporations, geoeconomic shifts, digitization, and the integration of ESG factors. Their findings highlight the growing complexity of global investment decisions and the increasing importance of sustainability in influencing foreign capital flows.

3 Model with fixed effects

The fixed-effects model is widely regarded as the preferred approach for panel data, particularly when observations span multiple time periods and entities, such as different countries over several years [19] Unlike other studies that employ cross-national panels, this study focuses exclusively on data pertaining to European Union member states.

To optimize the model, the fixed-effects framework is reframed as a time series analysis that captures changes within each entity over time [20]. This approach allows the dataset to be analyzed as if it were representing a single entity, accurately reflecting temporal variations. By doing so, the method aligns well with the principles of panel regression and provides robust predictions of entity-specific changes [21,22,23,24].

3.0.1 General Form of the Model

$$\text{FDI}_t = \beta_0 + \beta_1 \text{Carbon Intensity}_t + \beta_2 \text{ESG}_t + \beta_3 \text{WCI}_t + \beta_4 \text{Interest Rate}_t + \alpha + \varepsilon_t, \quad (1)$$

where:
Carbon Intensity: Data refers to carbon efficiency: the lower the value, the higher the efficiency
ESG : Environmental and, Social Governance
WCI : Working Conditions Index
Interest Rate : EU interest rates for the period 2017–2025
β_0 is the expected value of the dependent variable (Y) when all independent variables ($X_1, X_2, \ldots, X_k$) are equal to zero.
It represents the point where the regression line intersects the vertical axis (Y-axis) when all explanatory variables are zero.
β_1: regression coefficient
β_2 : It is the regression coefficient corresponding to the performance score variable in the environmental, social and governance standards.
β_3 : It is the regression coefficient corresponding to the Working Conditions Index variable.
α represents the baseline value of FDI at time t, which is not explained by the independent variables.
ε_t is the error term or residual at time t.

4 A Model of the Process Defined by Multiple Layers

The abbreviation ANN refers to the Multilayer Perceptron, which is often referred to as an MLP [22] [23].are employed in this study to enhance the accuracy of FDI estimation. Unlike fixed-effects regressions, which assume linear relationships between variables [24], the MLP can capture complex interactions among ESG components and the broader economic environment, including nonlinear patterns.

This capability allows the MLP to model intricate relationships that traditional linear models may fail to represent, making it particularly useful in contexts characterized by sudden shocks or crises, such as pandemics or energy disruptions. By accommodating nonlinear dynamics, the MLP provides a more nuanced understanding of how ESG factors influence FDI inflow.

4.1 General Form of the Model:

$$\text{FDI}_t = f(\text{Carbon Intensity}_t, \text{ESG}_t, \text{WCI}_t, \text{Interest Rate}_t) + \varepsilon_t, \quad (2)$$

where f is a nonlinear function represented by the neural network.

4.2 Network structure:

Input Layer: 5 inputs (including years)
Hidden Layers: Layer 1: 10 units, ReLU activation function. Layer 2: 6 units, ReLU activation function.
Output Layer: One unit (FDI value), linear activation function. The training function is formulated as

$$min_{(w,b)} \sum_{t=1}^{T} (Y_t - \widehat{Y}_t)^2, \quad (3)$$

where W weights, b biases, Y_t is the real value of FDI and $\widehat{Y}_t$ is the predicted value of FDI.

Table 1: The basic descriptive measures

	N	Mean	Sta. Dev.	SE of mean	Lower 95% CI of Mean
FDI	9	407.222	86.93069	28.9769	304.40138
ESG	9	1386.44	69.99929	23.09889	1333.17831
WCI	9	7.22E-4	3.414E-5	1.138E-5	6.96537E-4
Interestrate	9	1.6944	2.09082	0.96964	0.0873
Carbon Intensity	9	0.03303	0.0149	0.00497	0.02158

5 Results and Discussion

The relationship between ESG criteria and FDI flows is analyzed using a dataset of nine observations (N = 9) covering the period 2017–2025.

Table 1 presents the key descriptive statistics, which summarize the central tendencies, dispersion, and variability of the variables, as well as confidence interval estimates. These statistics provide a foundation for subsequent regression and predictive analyses by highlighting intrinsic variability in FDI patterns.

The average FDI inflow is estimated at 407.222 billion, with a standard deviation of 86.931 billion, reflecting substantial fluctuations over the study period. FDI dropped to 270 billion in 2020 but increased to 540 billion in 2021. The lower bound of the 95% confidence interval is 304.401 billion, indicating relative uncertainty due to the small sample size.

Regarding ESG performance, the average predicted score shows a standard deviation of 69.999 and remains relatively stable until 2023. In 2024, a marked increase to 1,509 is observed, indicating rapid improvement in sustainability capacity. The 95% confidence interval suggests that the true mean ESG value exceeds 1,333.178. The Workplace Conditions Index, representing labor quality, maintains a mean of 7.22 × 10207*b*2074 with a standard deviation of 3.414 × 10207*b*2075 up to 2023. The decline from 2024 to 2025, reaching 6.63 × 10207*b*2074, may result from coding adjustments or index redefinition, highlighting the need for careful verification of the index construction.

The average interest rate is 1.694%, with a standard deviation of 2.091%, reflecting considerable variation over time. A notable increase from 0% to 4.5% between 2021 and 2023 contributes significantly to this volatility. The lower bound of the 95% confidence interval is 0.087%, indicating that while the average rate is relatively low, it exhibits substantial temporal fluctuations.

These descriptive findings underscore the dynamic nature of FDI inflows and the variability in ESG performance and macroeconomic conditions across the EU. They provide a critical foundation for interpreting the results of the fixed-effects panel regression and MLP analyses that follow.

The study examines the evolution of investment, environmental, and social indicators from 2017 to 2025 using five time series charts. FDI inflows exhibit cyclical fluctuations during periods of economic disruption, with notable growth in 2021 followed by declines in 2022 and 2023. This expansion in 2021, from 270 billion to 540 billion, reflects a partial recovery from the COVID-19 pandemic. The subsequent decrease to 410 billion in 2022–2023 is attributed to the oil crisis and rising inflation. Investor confidence strengthened in 2024 and 2025, contributing to a steady rise in FDI.

Indicators of ESG performance show a generally upward trend over time. ESG ratings improved from 1.358 in 2017 to 1.509 in 2024, with a slight decline to 1.505 in 2025, potentially due to seasonal fluctuations or index recalibration. Carbon intensity, measured in tons of CO2082 per euro, decreased from 0.0295 in 2017 to 0.0246 in 2025, indicating a shift toward more sustainable energy sources and increasing environmental awareness. The Workplace Conditions Index rose from 0.000736 in 2017 to 0.000751 in 2023, followed by a drop in 2024 (0.000663) and a minor recovery in 2025, suggesting possible coding adjustments or index redefinition. The average interest rate remained at 0% from 2017 to 2021, then increased to 2.5% in 2022 and 4.5% in 2023, before declining to 3.75% in 2025, highlighting significant macroeconomic fluctuations that influence investment attractiveness.

The time series analysis demonstrates the interconnectedness of macroeconomic factors, environmental efficiency, labor conditions, and ESG performance in shaping FDI dynamics. Nonlinear trends and shocks, such as the pandemic and the energy crisis, expose the limitations of traditional linear models, emphasizing the value of advanced machine learning techniques like neural networks for improved forecasting and analysis.

Correlation analysis further reveals the relationships among key variables. Average Working Hours (AWH) is negatively correlated with GDP (-0.83) and the Workplace Conditions Index (WCI) (-1.0), indicating that more

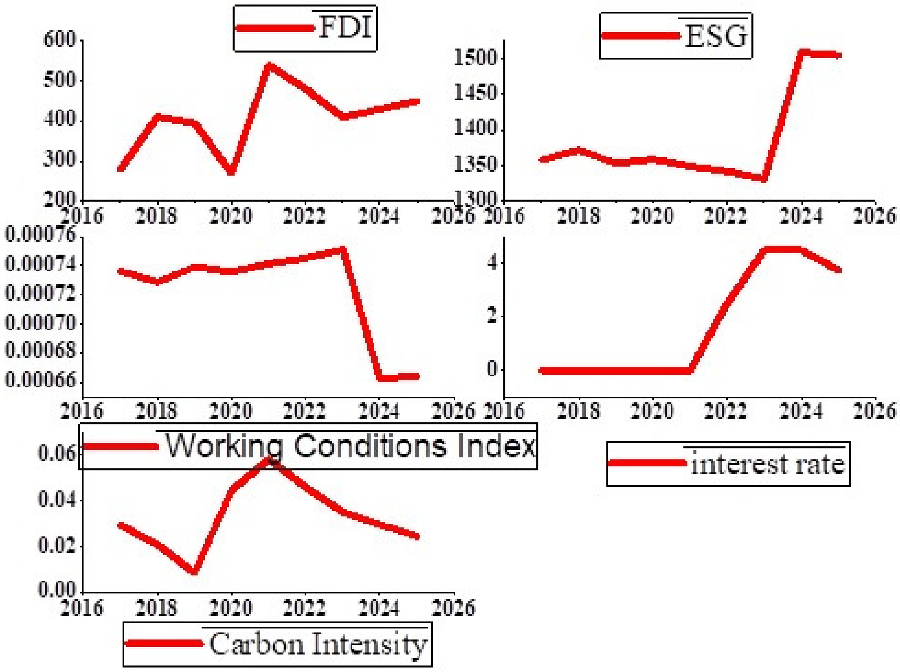

Fig. 1: Time series charts

Table 2: Regression Coefficients of Carbon

Model	Unstandardized Coefficients	Standardized Coefficients	t	Sig		95.0% Confidence Interval for B	
Constant	B	Std. Error	Beta			Lower Bound	Upper Bound
FI	480.581	921.2		0.5	0.6	1887	2848
CI	1834.361	2479.	0.314	0.7	0.4	-4538.	8206
W C	-212210	1278	-.083-	-.2	0.8	-34989	30745
IR	11.469	20.06	0.276	0.5	0.5	-40.	63.04

Table 3: Excluded Variable (ESG) and Collinearity Metrics in the FDI Regression Model

Excluded Variables						
Model		Beta In	t	Sig	Partial Correlation	Collinearity Statistics/Tolerance
FI	ESG	34.712b	.563	.604	.271	4.938E-5

developed countries tend to have shorter work hours and higher labor standards. Greenhouse gas emissions and carbon intensity exhibit an almost perfect correlation (0.99), reflecting the close alignment of environmental indicators. GDP shows positive correlations with WCI (0.84), ESG performance (0.64), and FDI (0.62), suggesting that economic development is associated with improved sustainability outcomes and higher investment inflows. In contrast, GDP has a weak correlation with Corporate Income (CI) (-0.27) and FDI (0.15), implying limited direct impact on carbon efficiency or capital inflows. Overall, these results highlight the complex interactions between ESG factors and FDI, illustrating how economic development, labor standards, and governance contribute to sustainable investment flows.

Fixed-Effects Model Fit

The p-values for all predictors exceed 0.05, indicating that none of the independent variables have a statistically significant effect on FDI at the 5% significance level. The wide confidence intervals, particularly for the Working Conditions Index, reflect substantial variability, likely due to the limited sample size or measurement differences

The coefficient for carbon intensity is positive (B = 1,834.361), suggesting a potential relationship between higher carbon intensity and increased FDI. However, this effect is not statistically significant (p = 0.493), and the confidence interval spans both negative and positive values, indicating considerable uncertainty. Similarly, the Working Conditions Index has a negative coefficient (B = -212,210.198), which implies a possible negative association with FDI. This effect is also not significant (p = 0.875). A small positive coefficient for the interest rate (B = 11.469) indicates that minor increases in rates might slightly enhance FDI, although this is likely influenced by dataset limitations, such as small sample size or high variability, as well as potential effects of unobserved factors like ESG performance, governance quality, and macroeconomic conditions.

ESG did not achieve statistical significance (p = 0.604 ¿ 0.05) and was therefore excluded from the final regression model. The extremely high standardized beta coefficient (34.712) is indicative of multicollinearity rather than a true effect. This is supported by a very low tolerance value (˜0.00005), suggesting that the ESG variable shares almost all of its variance with other predictors in the model, including carbon intensity, the Working Conditions Index, and interest rates. Consequently, ESG is considered redundant in the regression equation.

Machine Learning Process

The primary objective of this section is to apply the Multilayer Perceptron (MLP) model to the dataset used in this study. The network has a simple feedforward architecture, consisting of four input neurons, two hidden neurons, and one output neuron. Standardization is applied to ensure that variables with different scales contribute equally to the model.

The input features include Carbon Intensity, ESG performance, Working Conditions, and Interest Rate, while FDI serves as the output variable. The hyperbolic tangent activation function is used in the hidden layer, and an identity function is applied at the output layer, allowing the network to predict FDI as a continuous variable without transformation.

The choice of only two hidden neurons was deliberate, aiming to maintain simplicity and interpretability while avoiding an overly complex network. This configuration enables the model to capture basic nonlinear effects while minimizing the risk of overfitting. However, with just two hidden neurons, the network may struggle to represent more complex or higher-order interactions among the predictors.

Accurate performance and output

To evaluate predictive performance, a line chart and the RMSPE (Root Mean Square Percentage Error) metric are used. Figure 2 compares the performance of the fixed-effects model and the MLP neural network in predicting FDI flows.

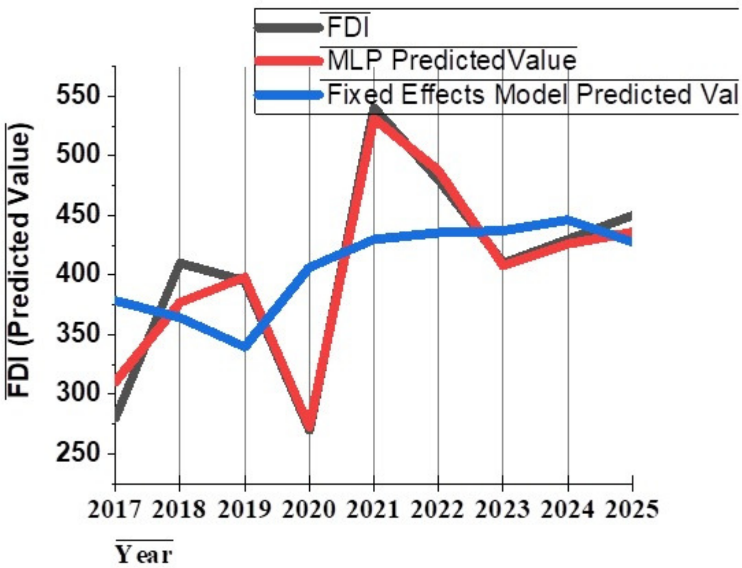

Fig. 2: The predicted value of the Models

The MLP model captures the 2021 peak with greater precision but exhibits notable fluctuations in other years, suggesting potential overfitting. In contrast, the fixed-effects model provides a more stable depiction of the data trajectory, although it is less responsive to unexpected shocks. The fixed-effects model is better suited for long-term forecasting, while the MLP model is particularly effective in capturing short-term fluctuations and nonlinear patterns in FDI.

Table 4: The performance of the models

	RMSPE
FEM	0.121047851
MLP	0.047143251

Root Mean Squared Percentage Error

$$RMSPE = \sqrt{\frac{1}{N}\sum_{i=1}^{n}\left(\frac{y_i - \hat{y}_i}{y_i}\right)^2} \times 100, \tag{4}$$

The RMSPE for the MLP model is substantially lower than that of the fixed-effects model (0.0471 vs. 0.1210), indicating higher predictive accuracy and fewer errors. The neural network outperforms the econometric model in capturing FDI variability, likely due to its ability to identify nonlinear relationships among the variables.

6 Conclusion and Policy Implications

This study provides insights into the relationship between ESG criteria and FDI flows in the European Union over the period 2017–2025. By combining advanced quantitative methodologies with machine learning approaches, the research offers a comprehensive understanding of the factors influencing investment attractiveness in the era of sustainable development.

The results demonstrate a complex, reciprocal relationship between ESG and FDI rather than a one-way effect. Improved ESG performance tends to attract more FDI, while FDI inflows themselves can enhance sustainability through the transfer of clean technologies, improvements in governance, and a better business environment. Correlation analysis indicates an inverse relationship between carbon intensity and FDI, suggesting that environmentally efficient countries are more attractive to investors. The positive association between ESG and FDI supports the notion that sustainability has become a factor in competitiveness. Although the link with the business conditions index is weaker, interest rates continue to exhibit a significant negative effect on investment attractiveness.

The fixed-effects model (FEM) indicated that most variables, including ESG, were not statistically significant (p ¿ 0.05). This outcome is likely due to the small sample size (n = 9) and substantial multicollinearity between ESG and carbon intensity, which makes it difficult to isolate individual effects.

In contrast, the Multilayer Perceptron (MLP) demonstrated higher predictive capacity. It accurately captured the 2021 peak in FDI despite fluctuations in other years and achieved a substantially lower RMSPE (0.0471 vs. 0.1210) compared to the fixed-effects model. These findings underscore the value of nonlinear models for evaluating the complex dynamics of investment flows and highlight the importance of machine learning in capturing interactions that traditional econometric models may miss.

Future research could expand on this study by employing larger and more detailed datasets to improve statistical power and reduce multicollinearity. Such datasets could include a broader range of environmental, social, governance, and firm-level FDI indicators. Moreover, exploring hybrid approaches that integrate econometric and machine learning models could provide deeper insights into the relationships between sustainability and investment patterns, particularly under economic shocks or climate policy interventions. These findings are particularly relevant for policymakers seeking to design strategies that promote sustainable development while attracting foreign investment.

References

[1] T. H. Ng, C. T. Lye, K. H. Chan, Y. Z. Lim, and Y. S. Lim, “Sustainability in Asia: The roles of financial development in environmental, social and governance (ESG) performance,” Social Indicators Research, vol. 150, no. 1, pp. 17–44, 2020

[2] A. S. Khodijah, “The influence of environmental, social, and governance performance on foreign investment,” Journal of Accounting and Investment, vol. 24, no. 1, pp. 64–83, 2022.

[3] A. Csordás and M. Al-Dalahmeh, “Developing trust, developing economies: The role of ESG disclosure in attracting foreign investment,” 2024.

[4] Ahmed, A. D., & Mourshed, M. (2018). Monetary policy and inflation in Sudan: An empirical analysis. Journal of Economics and Business, 93, 12-28.
[5] L. Ruan, J. Li, and S. Huang, "ESG rating adjustment and capital market pricing efficiency: Evidence from China," International Review of Economics & Finance, vol. 98, p. 103845, 2025.
[6] K. Narula, "'Sustainable investing' via the FDI route for sustainable development," Procedia - Social and Behavioral Sciences, vol. 37, pp. 15–30, 2012.
[7] N. Chipalkatti, Q. V. Le, and M. Rishi, "Sustainability and society: Do environmental, social, and governance factors matter for foreign direct investment?," Energies, vol. 14, no. 19, p. 6039, 2021.
[8] L. Lannutti, "The role of environmental, social and governance (ESG) regulations in attracting foreign direct investment(FDI)," in Proceedings of International Academic Conferences, no. 14216212, International Institute of Social and Economic Sciences.
[9] A. S. Khodijah, "The influence of environmental, social, and governance performance on foreign investment," Journal of Accounting and Investment, vol. 24, no. 1, pp. 64–83, 2022
[10] S. Wang, F. Chen, and X. Yang, "Environmental, social and governance performance: Can and how it improve internationalization of Chinese A-share listed enterprises," Heliyon, vol. 10, no. 13, 2024
[11] S. Bannour and N. A. Abdelkawy, "Sovereign ESG and foreign direct investment in the GCC: The amplifying role of trade openness in economic diversification," Sustainability, vol. 16, no. 21, p. 9326, 2024.
[12] L. Qing, A. A. Dagestani, E. Y. Nam, and C. Wang, "Does firm-level exposure to climate change influence inward foreign direct investment? Revealing the moderating role of ESG performance," Corporate Social Responsibility and Environmental Management, vol. 31, no. 6, pp. 6167–6183, 2024.
[13] D. F. Chrystella, S. Ibrahim, and Y. Lihua, "Maximizing the impact of foreign direct investment: Trends, determinants, and strategies for sustainable economic and social development," 2024.
[14] N. Zehouani and M. Ababou, "Mapping research trends on foreign direct investment and environmental sustainability," Discover Global Society, vol. 3, no. 1, pp. 1–20, 2025.
[15] M. A. A. Barral, "The nexus between trade and investment, ESG, and SDG," PIDS Discussion Paper Series, no. 2024-28, 2024.
[16] A. T. M. Faruq and M. A. R. Chowdhury, "Financial markets and ESG: How big data is transforming sustainable investing in developing countries," arXiv preprint arXiv:2503.06696, 2025.
[17] V. Kozulin, "The nature and classification of international investment in the era of globalization," ??????????, 2025, p. 182.
[18] T. D. Hill, A. P. Davis, J. M. Roos, and M. T. French, "Limitations of fixed-effects models for panel data," Sociological Perspectives, vol. 63, no. 3, pp. 357–369, 2020.
[19] N. Seetaram and S. Petit, "Panel data analysis," in Handbook of Research Methods in Tourism: Quantitative and Qualitative Approaches, pp. 127–145, 2012.
[20] O. T. Arowolo and M. I. Ekum, "Food production modelling using fixed effect panel data for Nigeria and other 14 West African countries (1990)," American Journal of Theoretical and Applied Statistics, vol. 5, no. 4, pp. 208–218, 2016.
[21] F. H. Astawesegn, V. Stulz, E. Conroy, and H. Mannan, "Trends and effects of antiretroviral therapy coverage during pregnancy on mother-to-child transmission of HIV in Sub-Saharan Africa: Evidence from panel data analysis," BMC Infectious Diseases, vol. 22, no. 1, p. 134, 2022.
[22] O. Soliev and M. Bakoev, "Econometric analysis and forecasting of FDI inflows using neural networks (AI)," ACUMEN: International Journal of Multidisciplinary Research, vol. 2, no. 5, pp. 11–17, 2025.
[23] I. Hilali-Jaghdam et al., "Comparative analysis of COVID-19 detection methods based on neural network," Computers, Materials & Continua, vol. 76, no. 1, 2023.
[24] M. M. Islam, A. Jannat, K. Aruga, and M. M. Rashid, "Forecasting foreign direct investment inflow to Bangladesh: Using an autoregressive integrated moving average and a machine learning-based random forest approach," Journal of Risk and Financial Management, vol. 17, no. 10, p. 451, 2024.