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Energy Dependence, Environmental Quality and Banking Sector Capital: New Evidence from OECD Countries

Angelo Leogrande [1,*], Fabio Anobile [1], Alberto Costantiello [1], Carlo Drago [2] and Massimo Arnone [3]

[1] LUM University Giuseppe Degennaro, Casamassima
[2] Unicusano University, Rome
[3] University of Catania, Catania
* Correspondence: leogrande.cultore@lum.it

Abstract

This article seeks to explore and analyze the interrelationship between environmental factors, the structure of the energy sector, and stability/resilience within the financial sector by employing data from OECD countries between 2004 and 2021. The article utilizes new data sets provided by the World Bank Group's Global Financial Development Data and Sovereign ESG Data, with specific emphasis placed on the bank capitalization indicator, which is described as the bank capital asset ratio, and is considered an important factor in sectoral stability/resilience. Using fixed effect panel data econometrics, the article suggests that methane emissions, PM2.5 air pollution, and net energy imports have statistically significant impacts on the bank capitalization process, while renewable energy and bank capitalization have positive and statistically significant associations. The positive association between fossil fuel consumption and bank capitalization suggests that there is an inherent contradiction between current sectoral stability/resilience and the challenges associated with the energy transition process. The Hausman test suggests that omitted variables may exist and that fixed effect econometrics is an appropriate model. Clustering analysis suggests that each country has an underlying regime driven by environmental factors, the structure of the energy sector, and sectoral stability/resilience. Moreover, machine learning regression analysis employing K-Nearest Neighbors (KNN) and Random Forest models indicate that significant predictive potential is possible and that energy dependence, renewable energy, and air pollution are important factors in bank capitalization processes. The article suggests that robust evidence is provided regarding environmental quality and its interrelationship with sectoral stability/resilience and has significant implications for developing macroprudential frameworks that incorporate elements of the energy transition process.

Keywords: climate risk; energy transition; banking stability; renewable energy; financial resilience

JEL: G21; Q54; Q43; C23; G28

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1. Introduction

In the recent past, the link between environmental sustainability, the energy transition, and financial stability has been a central concern in the research literature as well as in the policy debate. In the current environment, characterized by climate change, environmental degradation, and geopolitical risks in the energy sector, these issues have become prominent macro-financial risks that have the potential to redefine growth paths, investment patterns, and the stability of the financial system. In this context, banks occupy a central position. Banks, being the primary providers of credit to the real sector, are simultaneously exposed to environmental/energy risks as well as being the primary actors in the financing of the energy transition. In this context, the link between environmental/energy conditions and the stability of the banking system becomes a critical concern for regulators, supervisors, and policymakers. The global financial system is currently exposed to two types of climate change risks. The first type relates to physical risks, which are linked to the direct consequences of climate change, environmental degradation, or pollution. The factors that characterize these risks include extreme weather events, air pollution, long-run health, and productivity effects. These factors have the potential to dampen the macroeconomic environment, asset values, as well as the creditworthiness of the borrower, thereby affecting the banks' balance sheet. The second type relates to transition risks, which are linked to the energy transition, or the movement towards a more sustainable energy configuration. The energy transition risks include the impact of regulatory changes, technological innovation, asset revaluation, as well as changes in consumer behavior. In this context, the energy dependence of the macroeconomic system, coupled with the risks emanating from the international energy market, adds a further layer of macroeconomic risks, particularly in the current environment characterized by geopolitical risks in the energy sector. Significant research efforts have been devoted in recent years to different facets of the climate-energy-finance link. Some studies have emphasized, among other issues, the facilitating effects of finance, fintech, and green financial instruments on sustainable development, while others have focused on the effects of climate risks and environmental pressures on macroeconomic, corporate, or financial institution risk-taking. Another research direction has emphasized issues of sustainable finance governance, institutions, geopolitics, social, and distributional effects. More recently, researchers have pointed out the growing significance of digitalization, advanced analytics, and new data infrastructures in measuring, monitoring, and managing climate-related financial risks. Despite this significant research output, which covers a broad spectrum of issues, there are still gaps in this research area. First, many studies have either examined the effects of finance on sustainable development or, in turn, climate-related risks on specific financial institution behaviors, whereas fewer studies have directly examined the linkages between environmental conditions, energy structures, and significant financial sector resilience indicators. More precisely, although there is growing evidence on climate-related risks' effects on banks' risk-taking, valuations, or market performance, less is known about their effects on banks' capital buffers. Capitalization, usually defined as capital over total assets, is a crucial measure of financial sector resilience, reflecting a banking sector's capacity to withstand adverse shocks. Second, existing studies tend to analyze specific channels or instruments, such as green bonds, green banking strategies, or climate policy uncertainty, without embedding them into a unified framework that jointly accounts for environmental pressure, energy structure, and financial resilience. Such an absence of integration makes it difficult to jointly assess the relevance of physical risks, transition risks, and energy dependencies in maintaining banking sector stability. Third, while existing studies increasingly recognize the importance of accounting for cross-country heterogeneity, little attention has thus far been given to the possibility that countries could group into distinct structural regimes characterized by specific combinations of environmental quality, energy structure, and financial resilience. In other words, the link between sustainability and banking stability may not necessarily follow a linear and homogeneous pattern, but rather one that is based on specific development paths and trade-offs. Against this background, this study seeks to address an important research question: How do environmental conditions and energy structure influence banking sector resilience, as measured by bank capitalization, across OECD countries? In particular, do physical environmental risks, transition-related risks related to the structure of the energy mix, and dependencies related to external energy supplies tend to be systematically related to stronger or weaker bank capitalization? Do such potential linkages tend to follow linear and homogeneous patterns or rather exhibit non-linearities and structural regimes? To this end, the current paper proposes an integrated empirical framework based on the combination of three different, yet complementary, methodological approaches, i.e., panel data econometrics, clustering analysis, and machine learning regression models. This is the main methodological novelty of the current contribution, where panel data econometrics are employed to leverage the cross-country and time-series dimensions of the data set, comprising 38 OECD countries from 2004 to 2021, and accounting for unobserved country-specific heterogeneity using the fixed-effects approach. This approach provides the basis for the derivation of statistically grounded estimates of the average associations between environmental and energy variables and bank capitalization. Nevertheless, it might not suffice to capture the non-linear and complex interactions between climate, energy, and finance, which are at the core of the climate-energy-financial nexus. To this end, the current paper extends the analysis using clustering techniques, specifically the K-Means clustering approach, with the objective of identifying groups of countries characterized by different configurations of financial resilience, environmental pressures, and energy structures. This unsupervised machine learning approach enables the data itself to highlight different regimes characterized by specific trade-offs between financial and environmental resilience and energy security, respectively. Finally, the current paper applies machine learning regression models, including the Random Forest and the K-Nearest Neighbors approach, with the objective of examining non-linear associations and interaction effects, and the relative importance of different environmental and energy variables for bank capitalization. The latter approach is found to be appropriate for the analysis of macro-financial data and provides further insights regarding the relative importance of different aspects of the climate-energy nexus for financial resilience.

The remainder of the article is organized as follows. Section 2 reviews the relevant literature on climate risk, energy transition, and financial stability. Section 3 describes the data sources, variable selection, and the overall methodological framework. Section 4 presents the empirical model specification and discusses the panel regression results. Section 5 compares alternative clustering methods and introduces the K-Means-based regime identification. Section 6 reports the machine learning results, focusing on model performance and Random Forest variable importance. Section 7 integrates the empirical evidence and discusses the main findings on environmental risk, energy transition, and banking sector resilience. Section 8 derives the policy implications, emphasizing the integration of climate, energy, and financial stability policies. Finally, Section 9 concludes the article.

2. Literature Review

The current literature shows an increase in interlinking environmental sustainability, energy transition, and finance, especially with regard to the contributions of banks and markets. The first set of studies focuses on the facilitating role of finance and technology in environmental transitions. Khan and Shahid (2026) prove that FinTech and Green Finance have a positive joint effect on sustainable performance across countries. Dhar et al. (2026) emphasize that FinTech and GreenTech have strategic complementarity in South Asia. Bakhsh et al. (2025) use nonlinear analysis and prove that digital financial inclusion stimulates renewable energy consumption. Stöckel (2025) shows that digital monetary innovation, like central bank digital currencies, may cause unintended rebound effects in green policy. The above studies show that financial innovation is an important and ambiguous driver of environmental transition. The second set of studies focuses on integrating environmental change into broader processes of macroeconomic and social change. Labonté et al. (2026) discuss globalization and health in the framework of systemic change. Kumar (2025) offers empirical evidence of the effects of climate change on inflation and output in India. Algieri et al. (2025) prove that, in recent years, food inflation in developing countries is driven by climate change, speculation, and geopolitical tensions. The above studies show that environmental stress may affect financial stability indirectly by influencing economic growth, inflation, and distribution of income. Another set of research works focuses on the direct impact of climate risks on financial behavior. Tang and Fang (2026) show that extreme climate risks affect banks' risk-taking in 107 countries worldwide, which can be considered a strong relationship between environmental risks and financial behavior. Ramlall (2025) proposes the term 'financial footprint' and demonstrates its importance in the context of carbon emissions worldwide, which are related to financial behavior and banking activities. Moreover, Anwer et al. (2025) indicate the impact of climate policy uncertainty on the major financiers of the energy sector, which further confirms the close relationship between financial risks and policy risks. The second set of research works concerns the impact of sustainable finance

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instruments on financial behavior and risks. Azad and Tulasi Devi (2026) provide a comprehensive bibliometric and meta-analysis of green bonds worldwide, showing their rapid development and market evolution. Wan Zahari (2025) discusses the importance of green sukuk in the context of the World Bank's environmental and social policy, while Lyons and White (2025) examine the importance of green banks in generating multiple value streams in the context of the energy transition process worldwide. Tekin (2025) examines the importance of green banking strategies in the context of firms in Turkey, while Scherrer (2025) offers a theoretical perspective on the impact of sustainability on the mission drift of public sector banking, showing the negative impact of sustainability on banking behavior in general. Cianforlini (2025) examines European participation in the Asian Infrastructure Investment Bank's energy strategy, showing the importance of geopolitics in the context of sustainable finance worldwide. Fraccalvieri et al. (2025) offer a research work concerning the impact of governance and the importance of renewable energy in global banking. The importance of energy transition and energy dependence is another issue that is given significant emphasis in current studies. Tachy et al. (2026) conducted global research on the potential of banks in facilitating the energy transition in developed and emerging countries of the world, while Gigauri et al. (2026) focused their research on the OECD countries and its implications for economic prosperity and financial development. Omar et al. (2025) conducted their research in the MENA region and explored the interlinkages between energy transition, green growth, financial inclusion, and environmental degradation, revealing significant differences across countries of the region. Waidelich et al. (2025) scrutinized public credit provision and de-risking mechanisms in clean energy and emphasized the importance of learning spillovers in mobilizing finance. Current studies have also focused on exploring the interlinkages between technology, sectoral transformations, and environmental outcomes. Wang et al. (2026) revealed that smart 5G technology has significant associations with carbon emissions in various sectors and thus impacts environmental outcomes, while Kpadonou et al. (2026) conducted their research in West and Central Africa and explored climate-smart agriculture initiatives and their interlinkages with environmental outcomes. Coldrey et al. (2026) adds another dimension to these studies by presenting an investigation of financial needs to support a gender-responsive clean cooking transition, with some interesting links between social and environmental outcomes. Shanta and Adedokun (2025) and As-sya'bani et al. (2025) provide additional insights into the argument made above with their investigation of social sustainability drivers in coal-dependent economies and the fairness of energy transition between developed and developing countries, respectively. Some authors focus more explicitly on the links between finance, climate, and risk measurement. For example, Niedziółka (2026) examines bank performance with regard to AI, climate, and geopolitical risks, indicating that traditional bank performance has to take into account new dimensions of risk. For example, Zhao et al. (2026) discuss financial meteorology with regard to the Chinese context, indicating the relevance of weather and climate information for financial decisions. Another interesting contribution is made by Ahmad et al. (2026) with regard to an integrated green finance policy framework for a net-zero transition in Qatar, emphasizing the need for coordination between investment strategies. The common message is that, finally, climate and environmental risks are not peripheral anymore but form an integral part of financial policy and analysis. Despite the large body of literature, gaps remain, especially regarding the link between the natural environment, energy, and the key determinants of the banking sector's resilience, including capitalization. Although Tang and Fang (2026), Ramlall (2025), and Anwer et al. (2025) attempt to fill this gap, the emphasis in the majority of the literature is on risk-taking, emissions, and policy uncertainty. The large body of literature on sustainable finance instruments (Azad and Tulasi Devi, 2026; Wan Zahari, 2025; Lyons and White, 2025; Tekin, 2025) and sustainable finance governance (Cianforlini, 2025; Fraccalvieri et al., 2025; Scherrer, 2025) lacks empirical data on financial resilience, and the large body of literature on the macro and social impact of climate change (Labonté et al., 2026; Kumar, 2025; Algieri et al., 2025; Shanta and Adedokun, 2025; As-sya'bani et al., 2025) rarely attempts to create an empirical framework for the link between climate change and energy factors, and lastly, although the literature on digitalization and innovations (Khan & Shahid, 2026; Dhar et al., 2026;

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Bakhsh et al., 2025; Stöckel, 2025; Wang et al., 2026) is gaining momentum, the link between digitalization and innovations and banking sector resilience is not explored sufficiently.

Table 1. Main Strands of the Literature on Sustainable Finance, Energy Transition, and Financial Stability.

Macro-theme	Key References	Main Focus	Main Findings	Methods
Sustainable Finance, Green Instruments and Banking Strategies	Khan & Shahid (2026); Azad & Tulasi Devi (2026); Wan Zahari (2025); Tekin (2025); Lyons & White (2025); Scherrer (2025); Cianforlini (2025); Fraccalvieri et al. (2025); Ahmad et al. (2026); Gigauri et al. (2026)	Role of finance, green instruments, governance and banking strategies in the energy transition	Finance and fintech can support sustainability; green bonds, sukuk and green banks are expanding; governance and institutional setting shape banks' involvement; tensions may arise between sustainability goals and traditional banking objectives	Bibliometric analysis, qualitative institutional analysis, policy frameworks, cross-country comparative analysis, case studies, descriptive and conceptual approaches
Climate Risk, Energy Transition and Financial/Banking Risk	Tang & Fang (2026); Tachy et al. (2026); Ramlall (2025); Anwer et al. (2025); Lu & Wang (2025); Waidelich et al. (2025); Omar et al. (2025)	Impact of climate risks, energy transition and policy uncertainty on banks, firms and financial systems	Climate risks affect banks' risk-taking; banks differ in their capacity to finance the transition; financial activities shape emissions; policy uncertainty and stranded assets generate financial risk; public de-risking is crucial for clean energy finance	Panel data econometrics, cross-country regressions, firm-level empirical analysis, policy evaluation models, applied micro- and macro-finance methods
Macroeconomic, Environmental and Social Dimensions of the Transition	Labonté et al. (2026); Kumar (2025); Algieri et al. (2025); Shanta & Adedokun (2025); As-sya'bani et al. (2025); Coldrey et al. (2026); Kpadonou et al. (2026); Wang et al. (2026)	Broader macroeconomic, social, technological and sectoral impacts of climate change and sustainability policies	Climate change affects inflation, output and food prices; sustainability transitions have strong social and distributional effects; technological change and sectoral policies shape emissions; large cross-country heterogeneity emerges	Macroeconometric analysis, sectoral and policy evaluation, comparative analysis, case studies, interdisciplinary empirical and qualitative approaches
Digitalization, Innovation and New Risk Measurement in Sustainable Finance	Dhar et al. (2026); Bakhsh et al. (2025); Stöckel (2025); Niedziółka (2026); Zhao et al. (2026)	Role of digital finance, fintech, AI and climate data in sustainability and financial risk management	FinTech and digital inclusion can support renewable energy; digital tools may also create new policy risks; bank performance must account for climate and geopolitical risks; climate data increasingly enters financial decision-making	Nonlinear econometrics, conceptual and framework-based analysis, risk measurement approaches, applied financial

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		analytics, policy-oriented empirical studies

Note. The table synthesizes the main research streams linking sustainable finance, climate risk, energy transition, and digital innovation. While existing studies provide valuable insights, they rarely integrate these dimensions into a unified macro-financial empirical framework focused on banking sector resilience.

3. Data Sources, Variable Selection, and Methodological Framework

The selection and application of these variables indicate an integrated and methodologically robust approach, as they rely on two credible sources of data, namely, the Global Financial Development Database and the Sovereign ESG Database. The integration of these two sets of data increases the level of analytical capability, as it is possible to jointly examine the financial and environmental dimensions of economic performance, thus enabling a more comprehensive examination of the relationship between these sustainability-related variables and financial sector resilience.

CAP, as derived from data provided by the Global Financial Development Database, is considered an appropriate variable for application in the examination, as it directly measures the level of capitalization of the banking sector, thus enabling it to withstand possible losses. As supported by literature, CAP is extensively used as a variable to examine financial soundness and prudential financial systems, thus enabling the development of a benchmark for evaluating the relationship between financial sector resilience and external and structural factors. The remaining variables, as derived from the Sovereign ESG Database, are used as alternative measures of environmental pressures and energy structure, as they are identified as salient risk factors in the contemporary financial and economic environment. CH4P and PM25 are used as alternative measures of environmental pressures, with CH4P indicating methane emissions per capita, thus reflecting the level of associated financial risk due to a change in economic practice, and PM25 indicating exposure to PM2.5, thus reflecting physical environmental pressures. The combined effect of these two sets of variables presents a comprehensive picture of the relationship between environmental pressures, economic performance, and financial system stability.

The variables of FOSS and RENC are used in measuring the composition of the mix of energies, distinguishing between fossil fuels and renewable energies, thus making them significant in assessing exposure to costs related to risk transition. The newly introduced variable of ENIM adds another layer of importance as it measures the level of dependency on imported energies, thus allowing the model to incorporate exposure to costs related to environmental degradation and energy dependency, thus providing a holistic view. As a result, the sample is limited to OECD countries due to data quality, while the period of 2004-2021 is significant as it captures major events, including the global financial crisis and the development of climate change mitigation strategies. The variables selected have significant backing and are more relevant in assessing the interrelationship between environmental sustainability, the energy sector, and banking system stability. See Table 2.

Table 2. Variables Used in the Empirical Analysis: Financial, Energy, and Environmental Indicators.

Acronym	Variable name	Description
CAP	Bank capital to total assets (%)	Measures the capitalization of the banking sector and its ability to absorb losses. Higher values indicate stronger buffers, greater resilience to shocks, and improved financial stability, making it a key indicator of banking system soundness.
CH4P	Methane emissions (per capita)	Captures per capita methane emissions, a major greenhouse gas linked to agriculture and energy activities. It proxies environmental pressure and climate-related transition risk that can affect macroeconomic conditions and the stability of the financial and banking system.

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PM25	PM2.5 air pollution exposure	Measures population exposure to fine particulate matter, reflecting air quality and physical environmental risk. Higher exposure is associated with health costs, productivity losses, and economic stress, which may indirectly weaken banking sector performance and capital buffers.
FOSS	Fossil fuel energy consumption	Indicates the share or intensity of energy consumption based on fossil fuels. It reflects the structure of the energy mix and potential transition risk, as economies more dependent on fossil fuels may face higher adjustment costs in decarbonization processes.
RENC	Renewable energy consumption	Measures the use of renewable energy sources in total energy consumption. It proxies progress in the energy transition toward cleaner production, often associated with lower environmental risk, improved sustainability, and potentially stronger long-term financial and banking sector resilience.
ENIM	Energy imports, net	Captures a country's dependence on external energy supplies. Higher values indicate greater exposure to energy price and supply shocks, which can increase macroeconomic volatility and uncertainty, potentially affecting financial stability and banks' capitalization decisions.

Note. This table summarizes the dependent and explanatory variables employed in the empirical analysis, combining financial soundness indicators with measures of environmental pressure and energy structure to capture physical and transition climate risks and their links to banking sector resilience.

Descriptive statistics are used to describe the distributional characteristics of the variables CAP, ENIM, FOSS, CH4P, PM25, and RENC. The data set has a large number of observations. For FOSS and RENC, there are no missing values, but there are missing values in CAP and CH4P, as is common with panel data sets, especially with cross-sectional data for countries. As far as the central tendency is concerned, the mean of bank capitalization, CAP, is 7.827, and its median is 7.153. The distribution is slightly positively skewed, as supported by the positive skewness of 1.239. The high value of standard deviation, i.e., 2.905, indicates high variability in capitalization of the banking sector across countries. The distributional characteristics of ENIM are quite different from those of other variables. The mean of ENIM is 21.485, and its median is much higher at 55.443. The variable is left-skewed, as supported by its skewness of -3.949. The high value of kurtosis is another important distributional characteristic of ENIM. The high value of kurtosis indicates the presence of extreme negative values. The minimum value of ENIM is -726.181, indicating the possibility of extreme negative values of net import positions of some countries. The high value of standard deviation and high coefficient of variation of ENIM indicate high variability of ENIM, making it the most variable variable. Furthermore, the high mean and median values, which are above 70, suggest a high dependence on fossil fuels. The negative skewness suggests that there are a few observations at much lower levels. In the case of CH4P, though the mean and median values are relatively low, high positive skewness and kurtosis suggest that there are a few observations at much higher levels of methane emissions. PM25 has a fairly symmetric distribution with high dispersion and mild positive skewness, indicating a relatively homogeneous level of exposure in the included countries. RENC exhibits high dispersion with positive skewness, indicating that some countries have much higher levels of renewable energy consumption. Normality tests based on Shapiro-Wilk statistics clearly reject normality for all variables, which is in line with the above results. Overall, it suggests significant heterogeneity, asymmetry, and heavy-tailedness, particularly in energy dependence and environment-related variables, reflecting the heterogeneity of economic structures and energy consumption patterns in OECD countries over the period under consideration. See Table 3.

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Table 3. Descriptive Statistics of Financial, Energy, and Environmental Variables for OECD Countries.

Statistic	CAP	ENIM	FOSS	CH4P	PM25	RENC
Valid	590	667	684	646	646	684
Missing	94	17	0	38	38	0
Mode	4.800*	−726.181*	61.410*	0.232*	4.895*	7.300*
Median	7.153	55.443	75.640	0.966	13.517	16.300
Mean	7.827	21.485	72.459	1.406	14.402	20.692
Std. Error of Mean	0.120	4.946	0.697	0.057	0.231	0.616
95% CI Mean Upper	8.062	31.197	73.827	1.519	14.856	21.901
95% CI Mean Lower	7.593	11.773	71.092	1.293	13.948	19.483
Std. Deviation	2.905	127.740	18.218	1.458	5.873	16.105
95% CI Std. Dev. Upper	3.080	134.990	19.238	1.542	6.212	17.007
95% CI Std. Dev. Lower	2.748	121.233	17.301	1.383	5.569	15.294
Coefficient of variation	0.371	5.946	0.251	1.037	0.408	0.778
MAD	1.670	24.507	11.690	0.208	4.654	8.950
MAD robust	2.475	36.334	17.332	0.308	6.900	13.269
IQR	3.876	48.854	23.952	0.437	9.499	20.175
Variance	8.436	16317.485	331.885	2.126	34.487	259.370
95% CI Variance Upper	9.489	18222.326	370.102	2.379	38.583	289.237
95% CI Variance Lower	7.550	14697.513	299.317	1.912	31.012	233.918
Skewness	1.239	−3.949	−1.125	3.218	0.343	1.448
Std. Error of Skewness	0.101	0.095	0.093	0.096	0.096	0.093
Kurtosis	1.995	16.932	1.370	10.200	−0.954	2.318
Std. Error of Kurtosis	0.201	0.189	0.187	0.192	0.192	0.187
Shapiro-Wilk	0.915	0.503	0.920	0.545	0.956	0.873
P-value of Shapiro-Wilk	< .001	< .001	< .001	< .001	< .001	< .001
Range	18.357	836.369	89.750	8.076	23.481	82.100
Minimum	2.700	−726.181	10.250	0.204	4.895	0.800
Maximum	21.057	110.188	100.000	8.280	28.376	82.900
25th percentile	5.624	28.708	62.447	0.789	9.409	8.900
50th percentile	7.153	55.443	75.640	0.966	13.517	16.300
75th percentile	9.500	77.561	86.400	1.225	18.907	29.075
Sum	4618.203	14330.448	49562.150	908.293	9303.655	14153.300

Note. * Mode is computed assuming that variables are discrete. This table reports detailed descriptive statistics for banking, energy, and environmental indicators, highlighting substantial heterogeneity, skewness, and non-normality across variables, which reflects the diverse economic structures and energy profiles of OECD countries over the period considered.

From the methodological point of view, it combines panel data econometrics, clustering methods, and machine learning models in order to take into account the multiple and non-linear interrelations between environmental conditions, energy structure, and the resilience of the banking sector. Panel data methods are particularly suitable for tackling the research objectives in the current paper, given their ability to exploit both cross-sectional and time-series variations for 38 OECD countries over the 2004-2021 period. This structure increases sample size and efficiency of the estimator and allows for controlling unobserved country-specific effects, which might affect the results in a non-trivial fashion. However, linear panel data methods might not be sufficient for analyzing the non-linear interactions between the variables involved in the climate-energy-finance nexus. To overcome these concerns, clustering methods are used, which rely on unsupervised learning for identifying clusters of countries based on their financial sector resilience, environmental pressures, and energy structure configurations, without imposing any functional forms and threshold values for the variables involved. This is particularly relevant for the current research, given the non-linear relationship between sustainability and financial sector stability in any straightforward sense. In addition, the use of machine learning methods, and the random forest regression method in particular, is employed to further relax the assumptions related to the parameters and to account for the potential nonlinear relationships between the variables. The use of machine learning methods, and the random forest regression method in particular, is deemed appropriate for the present problem for several reasons: the method is robust against the problems of multicollinearity, outliers, and non-normality, as evidenced by the descriptive statistics presented above. Moreover, the use of machine learning methods, such as the random forest regression method, would allow for an assessment of the relative importance of the environmental and energy-related variables, providing an additional layer beyond the emphasis placed by the panel data modeling approach on the assessment of causality, and the emphasis placed by the clustering approach on the structural effects. The present approach, therefore, would be deemed a triangulation approach, where the panel data modeling approach would provide the statistical inference, the clustering approach would provide the structural effects, and the machine learning approach would provide the nonlinear effects, allowing for a comprehensive understanding of the relationships between the environmental risk, the energy transition, and the resilience of the banking system. See Figure 1.

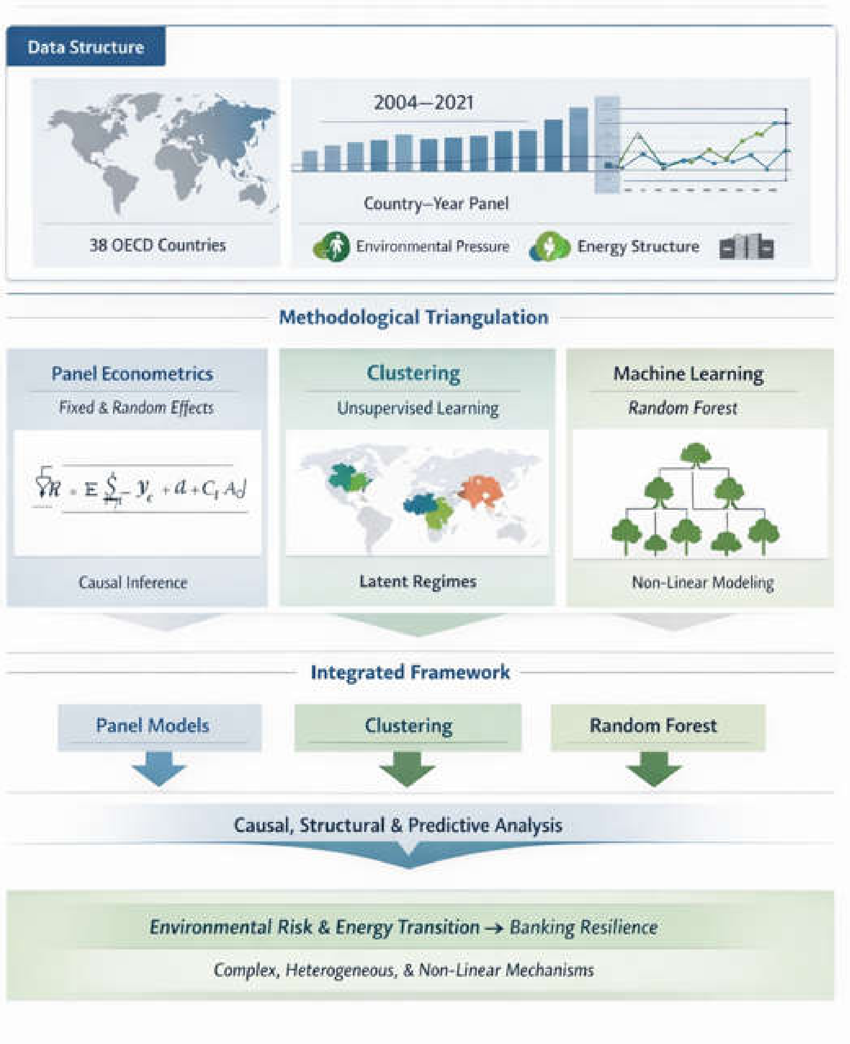

Figure 1. Integrated Analytical Framework: Panel Data, Clustering, and Machine Learning for Banking Resilience. The figure summarizes a methodological triangulation on 38 OECD countries (2004–2021), combining panel econometrics, clustering, and Random Forest to integrate causal, structural, and predictive analyses, showing how environmental risk and energy transition jointly shape banking sector resilience.

4. Empirical Model Specification and Panel Regression Results

The following model has been estimated:

$$CAP_{it} = \alpha + \beta_1(\mathrm{CH4P})_{\mathrm{it}} + \beta_2(\mathrm{PM25})_{\mathrm{it}} + \beta_3(\mathrm{FOSS})_{\mathrm{it}} + \beta_5(RENC)_{it} + \beta_6(ENIM)_{it}$$

$$i = 38\; t = [2004; 2021]$$

The purpose of this research is to explore the relationship between environmental/energy variables, on the one hand, and the resilience of the banking sector, on the other. The data used in this research comprise a panel dataset of 38 countries, with a total of 578 data points. The dependent variable in this research is CAP (Capital to Asset Proportion), a widely accepted proxy for the capitalization level in the banking system, as well as a proxy for the level of resilience in the banking system. In the context of climate change, the relationship between environmental/energy variables and the capitalization level in the banking system is a significant concern for financial system regulators. The empirical analysis in this research relies on five different variables, each representing a different aspect of environmental/energy variables, as well as their impact on the level of resilience in the banking system. The variables used in this research include CH4P (methane per capita), PM25 (exposure to air pollution), FOSS (fossil fuel energy consumption), RENC (renewable energy consumption), and ENIM (net energy imports). The fixed effect (FE) and random effect (RE) models are used in this research. The results of the Hausman test indicate that the fixed effect model is more suitable for the purpose of this research. From the theoretical point of view, the selection of the variables is well grounded. CH4P acts as a proxy for greenhouse gas emissions, incorporating general environmental pressures and transition risks related to climate change. PM25, in turn, measures physical environmental risks related to fine particulate matter in the atmosphere and can impact health outcomes, productivity, and consequently macroeconomic performance. FOSS and RENC measure the structure of the energy mix and differentiate between fossil and renewable energy sources. Finally, ENIM captures risks related to the dependence on external energy supplies, which can impact macro-financial stability. The results obtained from the regression analysis are quite interesting and consistent in both FE and RE models. First, the CH4P variable has a negative and statistically significant impact on bank capitalization in both FE and RE models, with values of -0.701 and -0.795, respectively. This implies that higher per capita methane emissions are related to lower bank capitalization ratios, which in turn suggests that high levels of environmental pressures and transition risks related to climate change tend to depress bank capitalization. Second, the PM25 variable has a negative and statistically significant impact on bank capitalization in both FE and RE models, with values of -0.234 and -0.218, respectively. This suggests that higher physical environmental risks related to air pollution tend to depress bank capitalization, which in turn might be related to negative health outcomes, productivity, and consequently macroeconomic performance and credit risk. Finally, the FOSS variable has a positive and statistically significant impact on bank capitalization in both FE and RE models, with values of 0.044 and 0.040, respectively. This might be counterintuitive in the context of long-run transition risks related to fossil fuel dependency in the energy mix of the countries in our sample. However, there are several plausible interpretations for this result. Countries with high levels of fossil fuel dependency might have developed industrial and financial systems that support high levels of bank capitalization in the short and medium term. Fourth, there is a positive and highly significant relationship between RENC and CAP, with coefficients of 0.115 (FE) and 0.105 (RE). This indicates that renewable energy consumption is positively related to bank capitalization. This is a significant policy implication, as it indicates that there is a positive relationship between the energy transition towards cleaner forms of energy and bank capitalization. Lastly, ENIM has a negative and statistically significant coefficient, with coefficients of -0.013 (FE) and -0.007 (RE). This indicates that there is a negative relationship between imported energy reliance and bank capitalization. This is consistent with the view that economies heavily reliant on imported energy experience macroeconomic instability due to their exposure to external price shocks, which can undermine the creditworthiness of borrowers and, in turn, negatively impact bank capitalization.

Regarding model performance, FE is found to explain a significant portion of country variations in CAP, as indicated by a high value of Within R^2 of 0.299 and LSDV R^2 of 0.823. The joint significance test of the explanatory variables is found to be statistically significant, as indicated by $F(5,535) = 45.72$, with a p-value of less than 0.0001. The test of individual effects rejects the null hypothesis of equal country-specific effects. However, the Hausman test (χ^2 (5) = 19.09, p = 0.00185) shows that we reject the null hypothesis that RE is consistent, implying that country-specific effects and regressors are correlated. Therefore, we can use FE as an alternative estimator, which implies that country-specific structural factors may be correlated with environmental and energy variables. From the diagnostic tests, we notice that econometric problems exist in the data set, which is common in macro-panel data sets. The problems include heteroscedasticity, non-normality of residuals, cross-section dependence, and serial correlation, as suggested by Wooldridge and Pesaran CD tests. However, we can still use coefficient estimates, as they remain significant, and use robust standard errors, which could include Driscoll-Kraay standard errors or panel-corrected standard errors. From the above analysis, we can see that an integrated view of environmental degradation (as measured by CH4P and PM25) and energy vulnerability (ENIM) is related to lower capitalization, while the energy transition (RENC) is related to higher capitalization. The relationship between FOSS and capitalization is questionable, as long-run risks associated with transition are high. From an economic policy viewpoint, we can see that climate and environmental factors should be taken into consideration when assessing financial stability. Therefore, promoting the energy transition and reducing pollution not only has positive implications for environmental sustainability but could also imply positive outcomes for banking system stability, at least in relation to capitalization. See Table 4.

Table 4. Environmental and Energy Determinants of Bank Capitalization.

Dependent variable: CAP		
Sample: 38 countries, 578 observations		
Variable	Fixed Effects (FE)	Random Effects (RE)
Constant	7.105*** (1.885)	7.201*** (1.878)
CH4P (Methane emissions per capita)	−0.701** (0.323)	−0.795*** (0.253)
PM25 (Air pollution exposure)	−0.234*** (0.033)	−0.218*** (0.031)
FOSS (Fossil fuel energy consumption)	0.044** (0.020)	0.040** (0.019)
RENC (Renewable energy consumption)	0.115*** (0.024)	0.105*** (0.022)
ENIM (Net energy imports)	−0.013*** (0.004)	−0.007** (0.003)
Model statistics		
	FE	RE
Observations	578	578
Countries	38	38
Mean CAP	7.686	7.686
Within R^2	0.299	—
LSDV R^2	0.823	—
Log-likelihood	−885.36	−1477.99
Durbin–Watson	0.547	0.547
Tests and diagnostics		
Joint significance of regressors (FE)	F(5,535) = 45.72, p < 0.0001	
Joint significance of regressors (RE)		$\chi^2(5)$ = 218.31, p < 0.0001
Test for individual effects (FE)	F(37,535) = 53.61, p < 0.0001	
Breusch–Pagan test (RE)		$\chi^2(1)$ = 1868.13, p = 0
Hausman test	$\chi^2(5)$ = 19.09, p = 0.00185 → FE preferred	$\chi^2(5)$ = 19.09, p = 0.00185
Heteroskedasticity (FE)	Chi-square(37) = 6205.8, p = 0	
Normality of residuals (FE)	Chi-square(2) = 111.677, p = 5.62e-25	
Normality of residuals (RE)		Chi-square(2) = 8.64021, p = 0.0133
Cross-sectional dependence (Pesaran CD, FE)	z = 13.3695, p = 9.11e-41	
Cross-sectional dependence (Pesaran CD, RE)		z = 13.9259, p = 4.41e-44
Autocorrelation (Wooldridge)	F(1,35) = 75.8792, p = 2.76e-10	F(1,35) = 75.8792, p = 2.76e-10

Note. Standard errors are reported in parentheses. Asterisks indicate statistical significance levels, highlighting the robustness of estimated relationships: *** p<0.01, ** p<0.05. The presence of stars signals economically meaningful and statistically reliable effects across model specifications.

5. Clustering Method Comparison and K-Means-Based Regime Identification

Table 5 shows the normalized performance of six clustering algorithms, i.e., Density-Based, Fuzzy C-Means, Hierarchical, Model-Based, K-Means, and Random Forest, in terms of six internal validation metrics, i.e., Maximum Diameter, Minimum Separation, Pearson's γ, Dunn Index, Entropy, and Calinski-Harabasz Index. Normalizing the performance of each algorithm within a given range, i.e., [0, 1], facilitates easy comparison among algorithms. Dunn Index and Minimum

Separation emphasize algorithms with high-quality clusters, i.e., compact clusters with high separability. Pearson's γ evaluates the correlation between distances and cluster assignments, which is closely related to the global structure. The widely used metric, i.e., Calinski-Harabasz Index, focuses on between- and within-cluster dispersion, which is an overall measure of cluster validity. On the other hand, Maximum Diameter and Entropy are minimized, indicating compact clusters and minimal within-cluster disorder, respectively. Based on the results, it can be noted that the Density-Based algorithm performs well in terms of separation-oriented metrics, achieving maximum performance, i.e., 1.000, in three metrics, i.e., Minimum Separation, Pearson's γ, and Dunn Index, indicating highly separated and compact clusters. However, significant underperformance in Entropy, i.e., 0.000, and low performance in the Calinski-Harabasz Index, i.e., 0.051, suggest that, in spite of high separability, the algorithm may not be able to achieve optimal results in terms of achieving balanced variance structure and high information content in the data set. Fuzzy C-Means performs very poorly in most of the evaluation metrics, i.e., almost 0, in terms of cluster separability. Fuzzy C-Means achieves maximum performance, i.e., 1.000, in Entropy, indicating that Fuzzy C-Means produces fuzzy clusters. Fuzzy C-Means performs very poorly in most of the evaluation metrics, i.e., almost 0, in terms of cluster separability. Fuzzy C-Means achieves maximum performance, i.e., 1.000, in Entropy, indicating that Fuzzy C-Means produces fuzzy clusters. Thus, Fuzzy C-Means is not suitable as a solution, as it does not focus

The results indicate that the Hierarchical Clustering algorithm presents a balanced performance, as it achieves satisfactory results in Pearson's γ (0.544), Entropy (0.764), and the Calinski–Harabasz Index (0.704), while performing moderately on the other criteria. In the case of Model-Based Clustering, the results indicate a balanced performance, as the algorithm achieves a high Entropy (0.915) while performing poorly on the other criteria. This indicates that the algorithm effectively captures the distribution, but the separation is poor. The results indicate that the K-Means Clustering algorithm achieves the best performance on the Calinski–Harabasz Index (1.000), as this criterion is considered informative in the context of the quality of the clusters. The algorithm also achieves a high Entropy (0.970) and a moderate Pearson's γ (0.471) compared to the other algorithms. However, the algorithm does not perform well on the Minimum Separation or Dunn Index criteria, although the overall performance presents a favorable trade-off between the criteria. The performance of the Random Forest algorithm is considered satisfactory on the Maximum Diameter (1.000) and Entropy (0.880) criteria, while the algorithm performs poorly on the other criteria, as indicated by the poor performance on the Calinski–Harabasz Index (0.165), reflecting the poor robustness of the clusters. Overall, considering all the criteria, the results indicate that the K-Means Clustering algorithm is the most favorable algorithm, as the Density-Based algorithms perform well on the separation criteria, while the K-Means algorithm presents the best performance on the Calinski–Harabasz Index, followed by a high Entropy. Thus, considering a consistent, interpretable, and well-structured data partitioning, the K-Means Clustering algorithm is the most preferred algorithm compared to the others. See Table 5.

Table 5. Normalized Clustering Performance Metrics across Alternative Algorithms.

Metric	Density Based	Fuzzy C-Means	Hierarchical	Model Based	K-Means Clustering	Random Forest
Maximum diameter	0.538	0.963	0.000	0.787	0.196	1.000
Minimum separation	1.000	0.000	0.124	0.046	0.031	0.062
Pearson's γ	1.000	0.000	0.544	0.173	0.471	0.292
Dunn index	1.000	0.000	0.216	0.041	0.057	0.048
Entropy	0.000	1.000	0.764	0.915	0.970	0.880

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Calinski–Harabasz index	0.051	0.000	0.704	0.277	1.000	0.165

Note. All metrics are normalized between zero and one to ensure comparability across methods. Although Density Based approaches perform best on separation-specific criteria, K-Means provides the most balanced solution, combining strong global variance explanation and high information content, as indicated by the highest Calinski–Harabasz index and near-maximum Entropy.

K-means clustering results show ten different clusters, implying large variability in terms of size and characteristics, and therefore a heterogeneous data structure. The size of the clusters ranges from a minimum of six for cluster 1 to a maximum of 131 for cluster 8, followed by a smaller maximum of 120 for cluster 9, implying the relative rarity of some configurations in comparison to dominant ones. The heterogeneity of the data structure is maximum for cluster 9, followed by cluster 8, cluster 6, and cluster 3, implying large contributions from these clusters to the data structure. On the other hand, the smallest relative contributions are from clusters 1, 5, and 10, implying more specific configurations. The silhouette values are an important tool for assessing the quality of the clusters, and high values for clusters 1 and 10 imply good cluster separation and homogeneity within the clusters. For clusters 2, 4, and 5, the silhouette values are moderate, while for clusters 3, 6, and 7, the values are smaller, implying more homogeneity within the clusters and smoother transitions between neighboring clusters, and therefore the existence of distinct regimes along with the more continuous components in the data structure. An analysis of the centers of each of these clusters shows that they exhibit significant differences in economic and environmental characteristics. Cluster 10 is characterized by an extremely high value of CAP, indicating good bank capitalization conditions, as well as high levels of renewable energy use and low levels of energy import dependence, indicating good conditions in terms of energy security as well. Clusters 7 and 6 exhibit relatively high values of CAP, while their characteristics in terms of energy and environmental security conditions exhibit significant differences, indicating alternative routes that countries may follow in order to achieve good banking sector conditions. On the other hand, cluster 5 is characterized by the lowest value of CAP and relatively high levels of methane emissions, indicating that environmental and banking sector conditions may be linked in an unfavorable way in this group of countries. The relatively large number of countries included in several of the clusters suggests that intermediate conditions exist in the data set. Cluster 9, which is one of the largest clusters, is characterized by relatively high values of CAP as well as high levels of PM2.5 exposure and fossil fuel dependence, indicating that countries included in this group exhibit development conditions that still heavily depend on polluting forms of energy use. Cluster 1, which is relatively small, is characterized by extremely high values of renewable energy use and low levels of fossil fuel dependence and pollution, while not exhibiting relatively high values of CAP. The clustering analysis suggests that environmental conditions, energy security, and banking sector conditions exhibit nonlinear relationships, with several regimes of countries exhibiting distinct trade-offs between environmental and banking sector conditions.

Table 6. K-Means Cluster Characteristics: Financial Resilience, Energy Structure, and Environmental Profiles.

Cluster	1	2	3	4	5	6	7	8	9	10
Size	6	26	98	23	26	79	52	131	120	17
Explained proportion within-cluster heterogeneity	0.002	0.096	0.167	0.048	0.018	0.175	0.103	0.183	0.195	0.012
Within sum of squares	1.356	75.423	130.843	37.830	14.145	137.094	80.853	143.415	152.195	9.160
Silhouette score	0.891	0.467	0.221	0.472	0.559	0.189	0.327	0.344	0.318	0.740
Center CAP	-0.364	-0.558	-0.322	-0.541	-1.001	0.625	1.293	-0.832	0.291	2.599
Center ENIM	-7.009	-1.341	0.312	0.094	-0.821	0.290	0.057	0.419	0.234	-2.553
Center FOSS	-1.051	0.511	-0.841	-2.482	0.101	-0.841	0.642	0.541	0.767	-0.002

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Center CH4P	-0.199	4.085	-0.283	-0.391	0.735	-0.352	0.255	-0.247	-0.356	0.134
Center PM25	-1.127	-1.315	-0.625	-1.428	-0.887	0.619	-0.841	-0.158	1.356	0.646
Center RENC	3.124	-0.213	0.394	2.167	0.232	0.943	-0.211	-0.764	-0.734	1.004

Note. The clustering reveals that the relationship between environmental conditions, energy structure, and banking sector resilience is non-linear, with countries grouping into distinct regimes characterized by different combinations of sustainability performance and financial robustness, reflecting heterogeneous development paths and structural trade-offs.

The K-Means clustering process identifies ten different groups with significantly different sizes and attribute values, which points to the heterogeneous nature of the data set. The sizes of the clusters vary from six in Cluster 1 to 131 in Cluster 8 and 120 in Cluster 9, which indicates the relative rarity or prevalence of certain configurations over others. The proportion of the data set's total structure, which is explained by the within-cluster heterogeneity, is the highest for Clusters 9, 8, 6, and 3, which points to the fact that these configurations are responsible for a large proportion of the data set's total structure. On the other hand, Clusters 1, 5, and 10 explain only a small proportion of the data set's total structure, which points to the fact that these are relatively rare configurations or more extreme profiles. The silhouette values are useful measures for evaluating the quality of the different clusters formed during the process. Clusters 1 and 10 have very high silhouette values, which point to the fact that these are very well separated and are more coherent from an internal perspective. Clusters 2, 4, and 5 have relatively moderate silhouette values, whereas Clusters 3, 6, and 7 have relatively lower values, which point to the fact that the transitions between these are more gradual and less heterogeneous in nature, indicating the presence of relatively more homogeneous structures in the data set. The cluster centers indicate the different economic and environmental differentiations present in the data set. Cluster 10 is characterized by an exceptionally high CAP value, implying strong bank capitalization, coupled with high levels of renewable energy consumption and low dependence on energy imports, thus implying strong financial and relatively energy-secure systems. Similarly, Clusters 7 and 6 are characterized by above-average CAP values, though with different energy and environmental configurations, thus implying alternative routes to strong banking sectors. In contrast, Cluster 5 is characterized by the lowest CAP values coupled with relatively high levels of methane emissions, thus implying a potentially vulnerable configuration where environmental and financial pressures are closely linked. The large clusters indicate intermediate configurations. Cluster 9, one of the large clusters, is characterized by moderately positive CAP values coupled with high levels of PM2.5 exposure and high dependence on fossil fuels, thus implying a development configuration still heavily dependent on polluting forms of energy. Cluster 1, though small, is of particular interest since it combines very high levels of renewable energy consumption with low levels of fossil fuel consumption and pollution, yet does not exhibit above-average bank capitalization values. Overall, the clustering analysis thus reiterates the non-linear character of the linkages between environmental conditions, energy structure, and banking sector resilience, with countries exhibiting different configurations with specific trade-offs between financial and environmental security. See Table 7.

Table 7. Standardized Cluster Centers from K-Means: Financial, Energy, and Environmental Profiles.

	CAP	ENIM	FOSS	CH4P	PM25	RENC
Cluster 1	-0.364	-0.199	-7.009	-1.051	-1.127	3.124
Cluster 2	-0.558	4.085	-1.341	0.511	-1.315	-0.213
Cluster 3	-0.322	-0.283	0.312	-0.841	-0.625	0.394
Cluster 4	-0.541	-0.391	0.094	-2.482	-1.428	2.167
Cluster 5	-1.001	0.735	-0.821	0.101	-0.887	0.232
Cluster 6	0.625	-0.352	0.290	-0.841	0.619	0.943
Cluster 7	1.293	0.255	0.057	0.642	-0.841	-0.211
Cluster 8	-0.832	-0.247	0.419	0.541	-0.158	-0.764

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Cluster 9	0.291	-0.356	0.234	0.767	1.356	-0.734
Cluster 10	2.599	0.134	-2.553	-0.002	0.646	1.004

Note. Clusters reveal heterogeneous regimes combining banking resilience, energy structure, and environmental pressure. Some groups show high emissions and weak capitalization, others strong renewable adoption with moderate financial strength, while large intermediate clusters reflect fossil-based development paths and non-linear trade-offs between sustainability and robustness.

The Figure 2 provides a complete summary of the results of K-Means clustering applied to the variables CAP, ENIM, FOSS, CH4P, PM25, and RENC, highlighting not only the determination of the optimal number of clusters, but also their internal structure. Panel A shows the evolution of the main fit criteria, AIC, BIC, and within-cluster sum of squares, with the number of clusters. All three indicators show a declining trend with increasing values of k, reflecting a mechanical improvement in fit with the addition of new clusters. However, the selected point at k = 10 highlights a reasonable trade-off in terms of model fit and model parsimony, indicating that a solution with ten clusters captures a significant part of the heterogeneity of the data without overfragmenting it. Panel B shows a two-dimensional projection of the data, with each cluster represented in a different color. The configuration of the plot suggests that several clusters are relatively well-defined, while others are less so, indicating a certain degree of transition between similar economic or environmental profiles. Overall, however, it points towards the existence of well-defined clusters, each corresponding to a particular combination of banking sector features, energy structure, and environmental conditions. A more direct economic interpretation is provided by panel C, where we find the standardized cluster means. Here, we can see distinct inter-cluster differences, especially with regard to CAP, FOSS, PM25, and RENC. For some clusters, we find high levels of bank capitalization accompanied by high levels of renewable energy and low levels of fossil fuels, indicating more sustainable and robust financial profiles. For others, we find low levels of capitalization accompanied by high levels of pollution and high levels of fossil fuels, indicating more vulnerable financial profiles. The diversity with regard to ENIM across clusters also points towards distinct levels of energy dependency on external sources. The Figure 2 above indicates that K-Means is a successful method in identifying relevant and interpretable regimes, capturing financial robustness, energy transition, and environmental pressures simultaneously. The above findings are in line with the assumption that there is not a uniform relationship between sustainability and financial robustness, but rather distinct typologies, each with their own financial and developmental trade-offs. See Figure 2

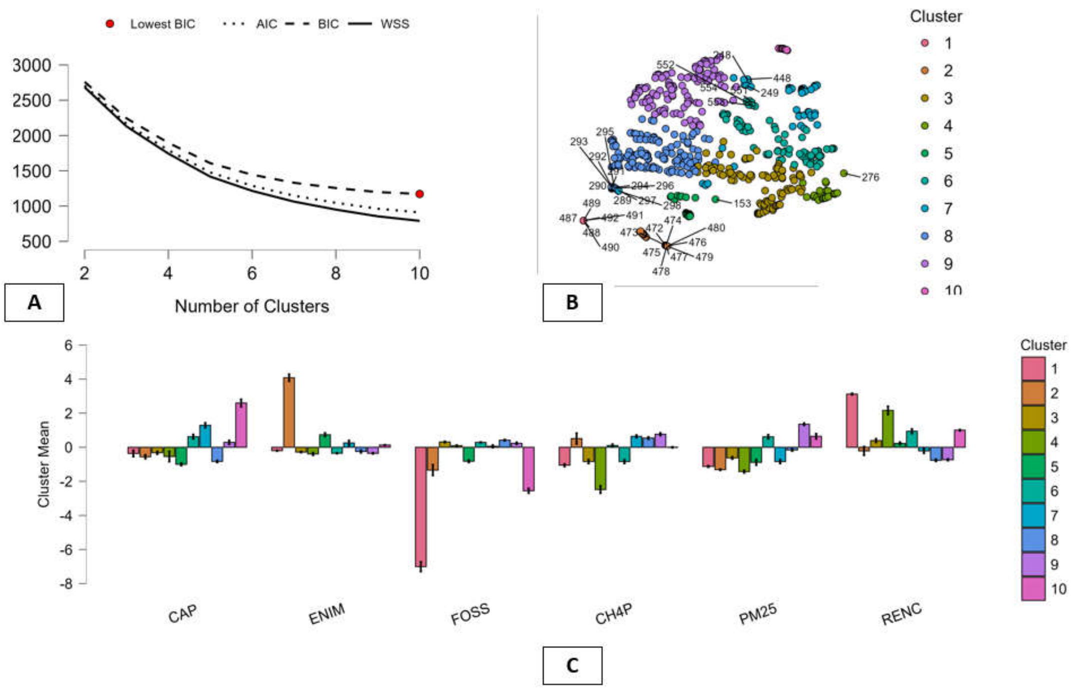

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Figure 2. K-Means Clustering of Banking Capitalization, Energy Structure, and Environmental Indicators. Panel A shows information criteria and WSS supporting a ten-cluster solution. Panel B displays cluster assignments in reduced space. Panel C reports standardized cluster means, highlighting heterogeneous regimes and non-linear trade-offs between financial resilience, energy dependence, and environmental pressure.

6. Machine Learning Performance Comparison and Random Forest Variable Importance Analysis

The table below illustrates the min-max normalized performance metrics for the predictive algorithms, with lower values representing better performance for error-based measures such as MSE, scaled MSE, RMSE, MAE/MAD, and MAPE, whereas higher values represent better performance for R^2. The error measures show a similar trend, with KNN having the best performance on all four error measures, with normalized values equal to zero for MSE, RMSE, MAE/MAD, and MAPE, and an almost zero value for scaled MSE. This implies that, out of the predictive algorithms, KNN has the lowest prediction errors, which are also relative errors, since they are presented on a percentage scale. The performance of the Random Forest algorithm is also good, with low normalized values for MSE, RMSE, MAE/MAD, and MAPE, although it does not achieve the minimum error levels as in the KNN algorithm. The performance of the Decision Trees algorithm is mediocre, with moderate error values, whereas the performance of the Boosting, Neural Networks, LASSO, and SVM algorithms is poor, with high normalized error values on most measures. The results obtained using the R^2 metric provide another viewpoint on the problem. It is clear that Random Forest has the highest normalized R^2 score, with KNN being very close behind. This means that both algorithms have strong explanatory power for the dependent variable. The explanatory power of Decision Trees is reasonable, while Boosting and Linear Regression have much weaker explanatory powers. LASSO and SVM have poor performance along this metric, indicating that these algorithms fail to capture the essential characteristics of the data. If we look at the results across all metrics, we can clearly observe that there is a trade-off between the two top-performing models: KNN and Random Forest. It is evident that KNN has significantly better predictive accuracy than the other models because it has the minimum errors across all metrics. Moreover, these errors are significantly lower than those of the other models. Therefore, these results suggest that KNN has better out-of-sample performance than the other models. On the other hand, Random Forest has the highest goodness-of-fit metric among all models while still having very low error rates, although these are higher than those of KNN. All other models are significantly outperformed by these two models and are thus not strong alternatives to these models. Thus, a fair assessment of the results obtained using all metrics may suggest that the best-performing algorithm among the ones presented is actually KNN because it has the lowest errors across all loss functions while still achieving a high R^2 metric. This means that the predictions obtained using the KNN algorithm are the most accurate and reliable among the ones obtained using the other models. Thus, KNN may be viewed as the most accurate algorithm among the ones presented here, while Random Forest may be viewed as the second most accurate algorithm because of its ability to achieve the highest R^2 metric among all models while still having low error rates. See Table 8.

Table 8. Min–Max Normalized Prediction Performance of Alternative Machine Learning and Econometric Models.

Metric	Boosting	Decision Tree	KNN	Linear Reg.	Neural Net	Random Forest	LASSO	SVM
MSE	0.744	0.403	0.000	0.946	0.675	0.117	0.681	1.000
MSE (scaled)	0.560	0.209	0.004	0.570	NaN	0.000	1.000	0.962
RMSE	0.813	0.517	0.000	0.962	0.759	0.186	0.763	1.000

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MAE / MAD	0.847	0.385	0.000	1.000	0.874	0.169	0.792	0.985
MAPE	0.877	0.310	0.000	0.943	1.000	0.107	0.773	0.854
R^2	0.303	0.699	0.993	0.293	NaN	1.000	0.000	0.017

Note. All metrics are min–max normalized to ensure comparability across models. Lower values indicate better performance for error measures, while higher values indicate better fit for R^2. Results show KNN minimizes prediction errors, whereas Random Forest achieves the highest explained variance.

These results provide a number of importance measures for the predictors in the Random Forest regression model. These measures indicate the level to which each predictor contributes to explaining the dependent variable, CAP. The three measures of importance are mean decrease in accuracy, total increase in node purity, and mean dropout loss. Regardless of the measure used to evaluate importance, it is clear that ENIM and RENC are the most important predictors. ENIM is seen to have a very high level of mean decrease in accuracy. This means that the predictive accuracy of the model drops considerably when this predictor is removed from the analysis. This indicates that bank dependence on net imports plays a very important role in explaining the differences in bank capitalization levels. This is likely to be because the macroeconomic environment is heavily influenced by bank dependence on net imports. RENC also shows very high importance levels in explaining the dependent variable. This is seen through the highest mean decrease in accuracy and also through the total increase in node purity. This shows the importance of the dimension of the energy transition in explaining the balance of the banking system. The level of renewable energy consumption in total energy consumption is seen to play an important role in explaining the balance of the banking system. PM2.5 is also high across all three importance measures, which further verifies that exposure to air pollution is not only an environmental, but also an economic predictor. The high importance of the PM2.5 variable also indicates that the relationship between physical environmental risk and health-related externalities and macroeconomic performance and financial stability is significant, thus impacting bank capital buffers. FOSS and CH4P are also significant, although to a lesser extent than the other variables. The lower mean decrease in accuracy and lower increase in node purity for the FOSS variable indicate that the model benefits from the inclusion of fossil fuel energy consumption, although the marginal impact is somewhat lower than that of the other variables. The intermediate level of importance attached to the CH4P variable indicates that methane emissions also play a role as an environmental pressure and transition risk, although the information contained within the CH4P variable is somewhat correlated with the information contained within the other variables. The importance measures therefore verify that the variables related to energy, the variables related to dependence on energy, and the variables related to local pollution are significant determinants of bank capitalization within the Random Forest model. This further verifies that transition risk and physical environmental risk play a role in financial stability, and that models of bank capitalization will be enhanced by the inclusion of the variables related to energy and the environment, as opposed to the traditional macro-financial indicators. See Table 9.

Table 9. Random Forest Variable Importance for Bank Capitalization (CAP).

	Mean decrease in accuracy	Total increase in node purity	Mean dropout loss
ENIM	3.703	303.219	1.858
RENC	3.791	280.948	1.888
PM25	3.530	275.180	1.840
FOSS	2.584	247.927	1.642
CH4P	3.302	230.137	1.703

Note. The table reports variable importance measures from the Random Forest model using mean decrease in accuracy, total increase in node purity, and mean dropout loss. Higher values indicate greater predictive relevance. Results highlight the central role of energy dependence, energy transition, and pollution exposure in explaining bank capitalization.

Therefore, these three measures, i.e., mean decrease in accuracy, total increase in node purity, and mean dropout loss, provide an overall and comprehensive analysis of the relative importance of each feature with respect to the model and problem being investigated. Among these features, ENIM and RENC stand out as being particularly significant, especially with respect to the mean decrease in accuracy, where ENIM shows an extremely large mean drop, emphasizing its crucial role in explaining the differences in bank capitalization, which may be attributed to some external factors related to energy that substantially impact the macro-environment and, hence, the balance of the banking sector. RENC is another feature that plays an important role, especially because it shows not only the largest mean decrease in accuracy but also an increased node purity, emphasizing its crucial role with respect to the energy transition dimension and that the share of renewable energy consumption plays an important role with respect to understanding bank capitalization and the balance of the banking sector. PM2.5, too, reveals significant importance with regard to all three criteria, thereby showing that the risk of air pollution is not only relevant from an environmental point of view but also extends to the economic sphere. The high level of importance reveals that physical environmental risk, as well as health-related externalities through the exposure to PM2.5, are highly correlated with economic performance and financial stability, which, in turn, affects the capital buffers of the bank. FOSS and CH4P, too, show significant importance, albeit lower compared to the previous factors. FOSS reveals lower mean decrease in accuracy and a higher node purity, thereby showing that fossil fuel energy consumption adds one more aspect to the model, albeit with a lower impact. CH4P reveals intermediate importance, thereby showing that methane pollution adds one more aspect to the model, albeit with a lower level of correlation with the other factors, which are related to energy consumption. Overall, these findings show that energy structure and dependence, along with local pollution, are important factors with regard to capitalization in the context of the Random Forest model, thereby showing that transition risk and physical environmental risk factors are important aspects with regard to financial stability, and therefore, the capital buffers of the banking sector should be modeled with regard to energy and environmental factors, too, rather than just relying on conventional macrofinancial factors. See Table 10.

Table 10. Local Contribution Decomposition of Random Forest Predictions for Bank Capitalization.

Case	Predicted	Base	ENIM	FOSS	CH4P	PM25	RENC
1	5.839	7.766	0.582	-0.599	-0.347	-0.672	-0.892
2	5.898	7.766	-0.274	-0.482	0.321	-0.543	-0.890
3	6.294	7.766	0.790	-0.684	-0.331	-0.396	-0.852
4	7.337	7.766	1.184	-0.387	-0.660	-0.655	0.089
5	7.333	7.766	1.419	-0.278	-0.783	-0.764	-0.028

Note. The table reports case-level decompositions of Random Forest predictions for CAP into baseline and variable-specific contributions. Positive and negative values indicate how energy dependence, energy mix, and environmental pressures increase or reduce predicted bank capitalization relative to the model baseline.

Figure 3 provides an overall view of the performance and internal workings of the Random Forest model used to interpret bank capitalization in relation to environmental and energy variables. Panel A shows the actual and predicted test values, and it appears that there is a good correlation between the two, with most of the points clustering closely together and forming a line close to the 45-degree line, showing that the model predicts well within an acceptable degree of accuracy. The fact that there is little variability in the actual and predicted values further shows that the model is able to predict the actual relationship between the variables. In Panel B, there appears to be a strong correlation between the out-of-bag mean squared error and the number of trees used to train the model, with the error reducing rapidly at first and then leveling off as the number of trees increases, a characteristic of Random Forests, where the reduction of error is most significant with an increasing number of trees. There is a strong convergence of training and validation errors, showing that there is no significant bias and variance. Furthermore, Panels C and D of the figure show that the total increase in node purity acts as an indicator of the importance of variables. In other words, variables that are more effective in reducing impurity when used to split the nodes are considered more important. In this case, it is evident that ENIM and RENC are more important than PM25, FOSS, and CH4P. This shows that the structure of the energy sector and the use of renewable sources of energy are important in explaining the differences in bank capitalization. In addition, it shows that the differences in pollution levels and the use of fossil fuels are of secondary importance. This is also evident from the mean decrease in accuracy, where RENC and ENIM are more important than the other variables. Overall, it is evident from the figure that the Random Forest model is not only proficient in dealing with classification problems but also produces results of significant economic importance. This shows that the stability of the banking sector is dependent on the transition in the energy sector and environmental factors. Thus, the results of the Random Forest model are in line with the hypothesis that financial stability cannot be achieved without the inclusion of environmental and energy factors. See Figure 3.

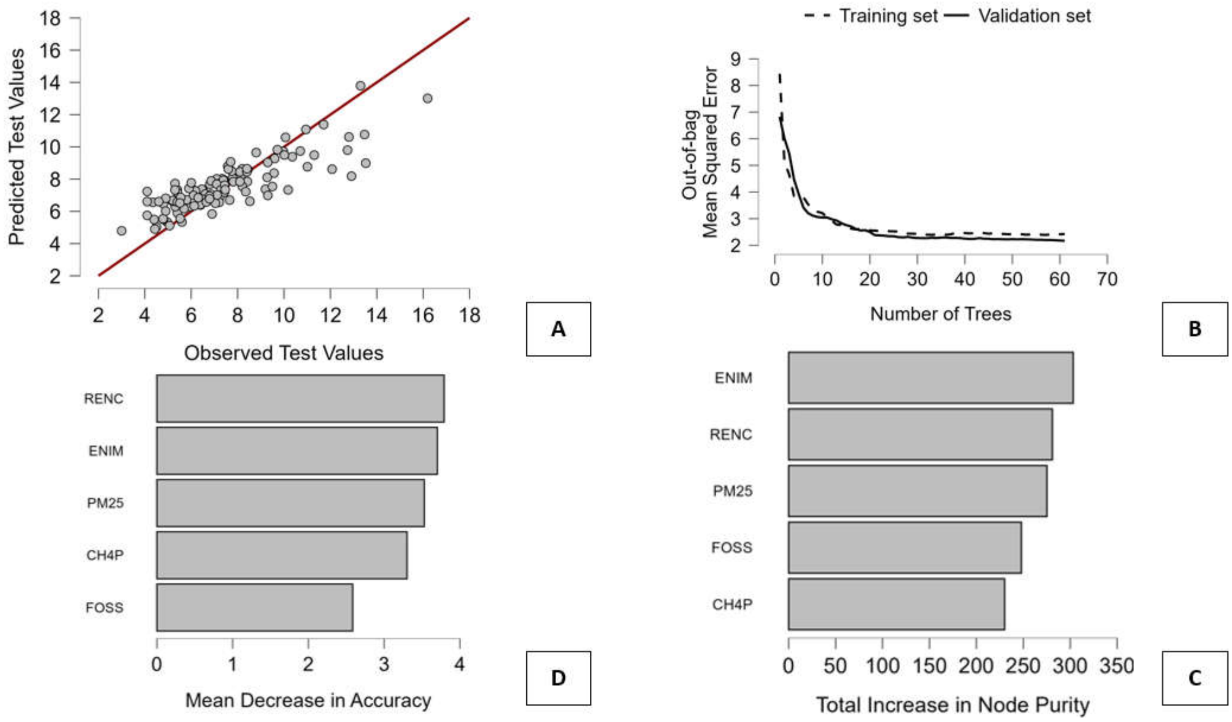

Figure 3. Random Forest Performance and Variable Importance in Explaining Bank Capitalization. The figure shows observed versus predicted values, convergence of out-of-bag error with increasing trees, and variable importance rankings. Energy dependence and renewable consumption dominate, confirming the central role of environmental and energy factors in predicting banking sector capitalization.

7. Integrated Empirical Evidence on Environmental Risk, Energy Transition, and Banking Sector Resilience

The empirical results show that there is a strong relationship between environmental conditions, the structure of the energy sector, and the resilience of the banking sector. The results from the panel regression analysis, which employed both Fixed Effects and Random Effects models, show that there are some significant relationships. The Hausman test results show that the Fixed Effects model is the most appropriate, as the unobserved characteristics of the countries are correlated with the regressors and must be controlled. In the Fixed Effects model, the negative and significant coefficients of methane emissions per capita (CH4P) and PM2.5 exposure (PM25) support the hypothesis that transition-related environmental and physical environmental risks, respectively, affect the level of bank capitalization. The negative and significant coefficient of net energy imports (ENIM) shows that the level of dependence on external sources of energy is associated with the level of bank

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capitalization. This also shows that the hypothesis that the banking sector will be affected by the macro-financial instability of the energy-import-dependent economies is true. The positive and highly significant relationship between renewable energy consumption (RENC) and CAP shows that the level of progress in the transition from traditional to alternative sources of energy is associated with the level of bank capitalization. This shows that the hypothesis that the banking sector will be affected by the level of progress in the transition from traditional to alternative sources of energy is true. The positive relationship between fossil fuel energy consumption (FOSS) and CAP is also interesting. This may seem counterintuitive but likely points to the continued importance of fossil-based industries in many of the OECD economies and their potential to provide support to profitability and asset prices in the short to medium term, even if it means higher transition risks in the longer term. The results from the clustering analysis provide another dimension to the results from the regression analysis. This analysis shows that the relationship between environmental variables and financial resilience through the energy structure is highly heterogeneous and nonlinear. The results from the K-Means algorithm used in the analysis indicate the presence of ten clusters with very different characteristics. Some of the clusters have high levels of bank capitalization and also high levels of renewable energy uptake and low levels of energy import dependency. These are likely to represent more sustainable and financially resilient regimes. Other clusters have lower levels of bank capitalization and also higher levels of pollution exposure and fossil fuels dependency. These are likely to represent more vulnerable regimes in which environmental and financial risks are likely to compound each other. Large numbers of intermediate clusters indicate mixed paths of development in which financial resilience and environmental pressures coexist in varying degrees. These are characterized particularly by high levels of exposure to PM2.5 and fossil fuels dependency. This suggests that countries are not likely to follow linear paths from "brown and fragile" to "green and resilient." This analysis suggests that countries are likely to occupy distinct regimes in which trade-offs between sustainability and financial resilience are likely to vary in very distinct ways. The results from the machine learning analysis also provide strong support to the analysis from the regression analysis and the clustering analysis. Of the three machine learning models used in the analysis, it is evident from the results that KNN and Random Forest are better models than the others. Of these two models, the results from the KNN model indicate the lowest levels of prediction errors and also the highest levels of explained variance. The results from the Random Forest analysis indicate that ENIM and RENC are more important variables in determining bank capitalization levels than the other variables. PM25 is also very important in determining bank capitalization levels. This verifies that energy dependence, the energy transition's advancement, and local pollution exposures are significant factors in determining financial resilience. The consumption of fossil fuels and methane emissions are also important, but their marginal contribution is relatively lower once the overall structure of energy and pollution is considered. Overall, the results paint a picture of a clear narrative. Environmental degradation and energy vulnerability are related to a weaker level of capitalization of the banking sector, while a shift towards renewable energy is related to a higher level of financial resilience. At the same time, the clustering results highlight the idea that these relationships are grouped into specific regimes. The policy implications of the results are clear. Environmental and climate policies are not only important from an environmental perspective but also from a broader macroprudential policy point of view. They are essential in order to enhance the overall resilience of the banking system. See Table 11.

Table 11. Synthesis of Empirical Evidence from Panel Regression, Clustering, and Machine Learning Approaches.

Method	Focus	Key Variables /Patterns	Main Findings	Interpretation
Panel Regressio	Causal/associational effects on CAP	CH4P, PM25, ENIM, FOSS, RENC	CH4P, PM25, ENIM have negative and significant effects on CAP; RENC has a positive	Environmental pressure and energy dependence weaken bank capitalization,

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n (FE preferred)			and significant effect; FOSS shows a positive short-run association; Hausman test favors FE	while renewable energy supports financial resilience; fossil fuels may still support capital in the short run but imply transition risks
Clustering (K-Means, k=10)	Identification of structural regimes	CAP, ENIM, FOSS, CH4P, PM25, RENC	Countries group into distinct clusters with heterogeneous profiles; some clusters combine high CAP and high RENC, others show low CAP with high pollution and fossil reliance; large intermediate clusters reflect mixed regimes	The relationship between sustainability and financial resilience is non-linear; countries follow different development paths with specific trade-offs between environmental quality, energy structure, and banking stability
Machine Learning (KNN, Random Forest)	Prediction and non-linear relationships	ENIM, RENC, PM25, FOSS, CH4P	KNN minimizes prediction errors; Random Forest achieves highest R^2; Variable importance ranks ENIM and RENC as most influential, followed by PM25	Energy dependence and energy transition variables are the strongest predictors of bank capitalization; environmental and energy factors play a central role beyond traditional linear effects

Note. The table summarizes and compares results from econometric, clustering, and machine learning methods, highlighting consistent roles of environmental pressure, energy dependence, and renewable energy in shaping bank capitalization, and emphasizing complementary insights on causality, heterogeneity, and predictive performance.

The Figure 4 represents a clear and coherent summary of the main results related to the relationship between environmental conditions, energy structure, and banking sector resilience, translating the results obtained through econometric models and machine learning techniques into a unified visual narrative. At its center, the concept of “drivers of banking resilience” highlights three main drivers with opposite directions of impact. On the left side of the figure, “sustainability boost” illustrates how higher renewable energy consumption correlates with higher bank capital buffers because clean energy is seen not only as a driver of sustainable development but also as a driver of financial stability. On the opposite side of the figure, “pollution penalty” illustrates how higher methane emission levels and higher exposure to PM2.5 have a negative impact on bank capitalization because these are seen as drivers of economic loss related to environmental degradation. In the intermediate region of the figure, “energy import vulnerability” illustrates how higher levels of net energy imports are seen as drivers of loss related to geopolitical tensions affecting bank resilience. The lower part of the figure also serves to introduce the structural and non-linear aspects of the results. The "green and resilient model" refers to country configurations characterized by high levels of bank capitalization, strong levels of renewable adoption, and low levels of import dependence. This refers to a virtuous circle where sustainability and bank resilience are mutually reinforcing. The other lines of development illustrate the non-linear effects of relying on fossil fuels, which can be beneficial in supporting bank capitalization but, at the same time, increase the risks of a transition. The non-linear nature of the development is also visually represented through the different lines of development and their intersections, which refers to the non-linear results of clustering, where different groups of countries are distinguished based on their energy-financial trade-offs. The overall message of the figure is that bank resilience is a non-linear function of environmental quality and energy choices, and policies supporting the energy transition are good for both sustainability and bank stability. See Figure 4.

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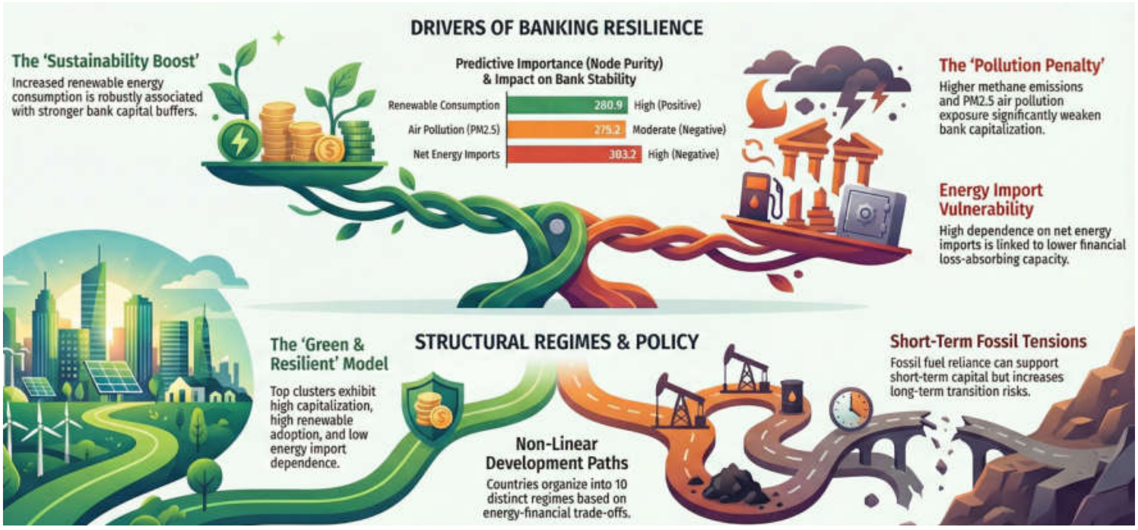

Figure 4. Random Forest Predictive Performance and Variable Importance for Bank Capitalization. Note. The figure integrates accuracy, error convergence, and variable importance from a Random Forest model, showing alignment between observed and predicted values, stabilization of out-of-bag error, and dominance of energy dependence and renewables in explaining capitalization.

8. Integrating Climate, Energy, and Financial Stability Policies: Implications for Banking Sector Resilience

The empirical results obtained in the current research have important implications for financial regulators, energy policymakers, and environmental authorities, emphasizing the importance of a more integrated approach to financial stability and sustainability. Based on the panel regression analysis conducted here, the negative relationship between bank capitalization and environmental pressure variables such as methane emissions and exposure to air pollution, as well as energy dependence variables such as net energy imports, are confirmed. At the same time, renewable energy consumption is shown to have a positive relationship with bank capitalization, while fossil fuel-based energy consumption appears to have a positive impact on bank capitalization only in the short term. Firstly, financial supervisors should integrate environmental and energy variables into financial supervisory practices. The negative relationship found here between bank capitalization and indicators of pollution implies that physical and transition climate change risks are likely to affect bank balance sheets. Financial regulators should thus incorporate scenarios related to environmental degradation into stress tests, capital adequacy assessments, and supervisory reviews to better assess the resilience of financial institutions to climate change risk events. By doing so, financial supervisors will be better equipped to identify financial institutions and countries that are most vulnerable to climate change risk events. Secondly, the strong influence of energy dependence, measured through net energy imports, highlights the importance of financial stability through energy security. For nations that are highly dependent on external sources of energy, the risk of geopolitical tensions and energy price volatility is higher, which may have spillovers to financial stability and the banking system. Thus, financial stability gains may be achieved through measures to enhance energy diversity, efficiency, and local energy production capacity. In such a context, energy security is seen to be integrated with financial stability. Thirdly, the positive relationship between renewable energy consumption and bank capitalization implies that speeding up the energy transition may be beneficial for financial stability. Investments in renewable sources are seen to be related to a financially stable and predictable economic environment, which is beneficial for bank capitalization. Thus, policymakers should be encouraged to persist with the promotion of renewable energy through a stable regulatory framework. The cluster results suggest that nations are likely to be following diverse development pathways and may face varying trade-offs between sustainability and financial

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stability. Such a diverse outcome requires a differentiated policy response instead of a generalized or "one-size-fits-all" approach to financial stability issues. For nations belonging to the cluster with high pollution levels and low bank capitalization, policymakers may need to adopt a more aggressive stance on environmental and energy reforms, while nations belonging to the cluster with higher bank capitalization and renewable energy may need to consolidate these gains and be proactive in managing transition risks. Lastly, the findings from the machine learning methods, such as the Random Forest and KNN models, suggest that the energy structure and environmental variables are some of the strongest predictors of bank capitalization levels. This, therefore, adds to the rationale for developing forward-looking policy instruments, which can be data-driven in nature. The supervisory authorities can invest more in collecting better data, incorporating ESG data into existing financial databases, and using more sophisticated data analysis methods to track these emerging risks. On the whole, the results indicate that the enhancement of the financial resilience of the banking sector and the promotion of the energy transition are mutually supportive goals. Concerted policy strategies to address environmental sustainability and financial regulation in tandem can help to improve economic stability in the longer term and minimize the risks of climate and energy-related shocks leading to financial crises.

9. Conclusions

The objective of this study is to examine the impact of environmental factors and energy structure on the resilience of the banking sector in OECD countries, with the bank capital to assets ratio used as a major metric for financial stability. The study uses a combination of panel data econometrics and machine learning-based regression analysis to achieve a comprehensive assessment of the impact of climate-energy dynamics on financial stability in the context of OECD countries from 2004 to 2021. The findings suggest that environmental degradation, along with energy structure, is not only a major sustainability issue but also significantly influences financial stability. The findings from the panel regression suggest that methane emission levels, which are high, are negatively correlated with bank capitalization, thereby emphasizing the importance of transition and physical environmental risks in the context of financial stability in OECD banking systems. Similarly, a high level of exposure to PM2.5 pollution is negatively correlated with bank capitalization, thereby emphasizing the importance of physical environmental risks in the context of financial stability in OECD banking systems. Moreover, a high level of net energy imports is also negatively correlated with bank capitalization, thereby emphasizing the importance of external energy shocks in the context of macro-economic stability in OECD countries. On the contrary, renewable energy consumption is positively correlated with bank capitalization at a highly significant level, thereby emphasizing the importance of the energy transition in the context of financial stability in the macro-economic environment of OECD countries. The positive association of fossil fuel consumption with bank capitalization may be due to the short- to medium-term importance of economic structures, wherein fossil fuels are important for financial stability in OECD banking systems. The clustering analysis adds depth to these findings by providing structural distinctions among the countries. The K-Means approach reveals ten distinct country groups with varying levels of financial resilience, energy structure, and environmental pressures. Countries with high levels of bank capitalization and high levels of renewable energy consumption show lower levels of energy dependency, whereas the remaining countries show lower levels of capitalization, high levels of pollution, and high levels of energy dependency. The intermediary clusters show countries with moderate levels of financial resilience and varying levels of environmental pressures, showing a range of overlapping financial and environmental resilience. The machine learning analyses confirm these findings. The K-Nearest Neighbors and Random Forest algorithms show better predictive performance compared to the remaining algorithms, with the KNN algorithm showing the least prediction error and the Random Forest showing the highest variance explanation. The variable importance of the Random Forest model reveals net energy imports and renewable energy consumption as the most important factors affecting bank capitalization, followed by PM2.5 exposure. These findings again emphasize the

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importance of energy dependency, the energy transition, and environmental pressures on financial resilience, which goes beyond the findings of the linear model. As such, the implication of the results of this paper is significant from a scholarly and policy-making point of view. In the former case, the paper shows the importance of using econometric methods and machine learning to identify the average and structural nonlinearities in complex financial and economic systems. In the latter case, it shows the importance of incorporating climate change and energy into financial stability. As such, reducing pollution levels and developing alternative sources of energy are not only important from an environmental point of view but also from the point of view of financial stability in the banking sector.

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