Check for updates

Business Strategy and the Environment

WILEY | Business Strategy and the Environment

RESEARCH ARTICLE OPEN ACCESS

Forecasting and Explaining Environmental Fiscal Capacity: How Informality and FinTech Shape Environmental and Biodiversity Finance

Sami Ur Rahman[1] | Muhammad Ibrahim Khan[1] | Javed Hussain[1] | Imran Ali Khan[2]

[1]Business School, Birmingham City University, Birmingham, UK | [2]Muhammad Ali Jinnah University, Karachi, Pakistan

Correspondence: Sami Ur Rahman (sami.rahman@bcu.ac.uk)

Received: 21 May 2026 | **Revised:** 4 October 2026 | **Accepted:** 9 October 2026

Keywords: biodiversity finance | FinTech | green finance | machine learning | shadow economy

ABSTRACT

This study examines the impact of the shadow economy (SE) on environmental fiscal capacity (environmental tax revenue, public environmental expenditure, and biodiversity expenditure) and the moderating role of financial technology (FinTech) across OECD countries over 2004–2022. Using second-generation econometric techniques, with robustness assessed through the CCEMG estimator, Driscoll–Kraay fixed effects, and one-step GMM, and complemented by machine-learning forecasting (tensor double machine learning and a graph-inspired machine learning model) compared using the Diebold–Mariano test. The analysis yields three main findings. First, the SE significantly reduces environmental tax revenue and public environmental and biodiversity expenditures, consistent with the hypothesis that informality constrains the fiscal capacity required for environmental protection. Second, FinTech adoption directly enhances environmental revenue and mitigates the adverse effect of the SE on environmental revenue through a transaction-formalization channel that expands the observable tax base, although its direct association with biodiversity expenditure is negative, reflecting a countervailing frontier-expansion effect. Third, the forecasting evidence reinforces this structural account: Environmental tax revenue is strongly forecastable and public environmental expenditure moderately so, whereas biodiversity expenditure resists accurate prediction across both models. Overall, the findings highlight the importance of digital financial innovation as a complementary instrument for reducing informality, strengthening environmental governance, and advancing biodiversity conservation in OECD economies.

JEL Classification: E26, G23, H23, Q56, C53

1 | Introduction

Meeting the financing commitments of the Paris Agreement (2015) and the Kunming–Montreal Global Biodiversity Framework depends on governments' fiscal capacity and tax revenue (OECD 2021; Horn et al. 2026). Environmental taxes generate revenue from environmentally harmful activities, whereas public environmental and biodiversity expenditures translate it into conservation and environmental protection outcomes. However, the effectiveness of both mechanisms fundamentally depends on a single structural precondition: a broad and observable formal tax base. The structural factor of interest here is the shadow economy (SE), defined as the market-based production of goods and services that deliberately evade taxation and regulation (Medina and Schneider 2019). The SE averaged roughly 16% of GDP across OECD countries in 2022, ranging from about 5.4% in Switzerland to roughly 32% in Turkey (F. Schneider 2022).

This is an open access article under the terms of the Creative Commons Attribution License, which permits use, distribution and reproduction in any medium, provided the original work is properly cited.

© 2026 The Author(s). *Business Strategy and the Environment* published by ERP Environment and John Wiley & Sons Ltd.

The current study examines how SE affects the fiscal capacity that funds environmental programs and biodiversity policy and whether financial technology (FinTech) moderates this relationship.

This question is particularly important because fiscal stakes are large and the financial shortfalls are severe. Approximately 80% of global biodiversity finance is based on domestic public budgets, whereas current public biodiversity spending of around US$121 billion annually remains below the estimated US$598–824 billion annual financial requirements (Deutz et al. 2020; BIOFIN 2024). SE is expected to constrain public environmental finance in two distinct ways. The domestic public budget is the main source of public environmental finance; however, structural factors that reduce fiscal capacity may limit the government's ability to implement environmental and biodiversity policies. Existing literature has extensively highlighted the significance of SE in emissions and ecological footprint (Biswas et al. 2012; Dada et al. 2021; Baloch et al. 2022); however, it remains unexplored whether SE affects public finance for environmental protection and biodiversity conservation. SE may not only affect environmental dynamics but also environmental fiscal capacity, thereby affecting environmental quality and biodiversity conservation.

The SE causes an asymmetric environmental effect. On the preventive side, it reduces environmental tax revenue and expenditure by increasing informality (fiscal capacity channel) (S. U. Rahman et al. 2026), causing weak enforcement, limited administrative capacity, and lower regulatory quality (Dreher and Schneider 2010). On the remedial side, which includes biodiversity expenditure, SE increases fiscal demand. The main causes of biodiversity loss, such as illegal logging, artisanal mining, unlicensed harvesting, and unmonitored land conversion, are highly concentrated in the informal sector, which produces an ecological footprint that the government needs to remediate (Brashares et al. 2014; Nellemann et al. 2016). This causes a self-reinforcing, fiscally inefficient low-conservation equilibrium: The revenue base for prevention shrinks, as the demand for costly remediation expands. This phenomenon is the study's main theoretical contribution, which distinguishes it from prior studies that focus on the SE's environmental impacts. It is argued that SE not only determines environmental quality but also serves as a structural barrier, which restricts public environmental fiscal capacity (S. U. Rahman et al. 2026; Bitassa et al. 2025).

To counter the impact of SE, this framework incorporates the significance of FinTech in the proposed frameworks (S. U. Rahman et al. 2023; Syed et al. 2021). FinTech, which includes online and mobile payments, credit cards, debit cards, ATMs, and point-of-sale terminals (Kshetri and Loukoianova 2019), has largely expanded across OECD economies (Sahay et al. 2020). By replacing cash transactions, increasing the traceability of cash flows, and lowering the cost of formal participation, FinTech discourages informal activity and promotes formalization (M. M. Rahman 2023). The fiscal implication is direct: By enlarging the observable tax base and strengthening regulatory compliance and monitoring, FinTech reinforces the revenue foundation on which environmental fiscal capacity depends. Therefore, it may moderate the fiscal damage caused by SE on these outcomes.

Accordingly, this study examines the SE–environmental fiscal capacity relationship, while considering the moderating role of FinTech in a balanced panel of OECD countries, from 2004 to 2022. Several econometric techniques are employed, including common correlated effects mean group (CCEMG), one-step generalized method of moment (GMM), and Driscoll–Kraay fixed effects. The CCEMG is the primary estimator because it controls cross-sectional dependence (CSD) and slope heterogeneity in the panel (Pesaran 2006). The one-step GMM and Driscoll–Kraay fixed effects are used for robustness checks, whereas the Dumitrescu and Hurlin (2012) test is employed to assess directional causality among the variables.

Further, the study explains how much of the variation in each fiscal outcome is structurally predictable, as opposed to being governed by idiosyncratic political-budgetary processes. The study complements its econometric analysis with two machine-learning forecasting approaches: tensor double machine learning (Tensor-DML) and a graph-inspired machine learning model (Graph-ML) to assess whether SE and informality carry predictive content for each fiscal outcome. The purpose is diagnostic: whether the preventive outcomes are more predictive than the discretionary remedial outcome. This combination of explanatory econometrics and predictive machine learning responds to a growing methodological debate that the two traditions are complementary rather than substitutes (Mullainathan and Spiess 2017; Athey and Imbens 2019; Storm et al. 2020).

The study contributes to literature in three ways: theoretically, empirically, and methodologically. Theoretically, it reconceptualizes the consequences of SE for environmental policy by introducing the concept of asymmetric environmental fiscal conditions, whereby preventive fiscal instruments (environmental tax revenue) and remedial fiscal instruments (environmental and biodiversity expenditures) reflect the SE impact differently. This concept is developed based on the within-country pollution-haven hypothesis and fiscal capacity theory. Empirically, the study disaggregates fiscal capacity into three theoretically distinct outcomes (environmental tax revenue, public environmental expenditure, and biodiversity expenditure) and shows that the SE does not act uniformly across these dimensions in the OECD countries. Further, the study introduces FinTech adoption as a structural moderator in these relationships to examine whether FinTech development moderates the SE impact on the green transition. Methodologically, the study integrates an econometric strategy robust to CSD and slope heterogeneity with a machine-learning forecasting layer, providing mutually independent corroboration that improves causal and structural inference.

2 | Literature Review

2.1 | SE and Environmental Fiscal Capacity

The relationship between SE and the environment has been extensively examined; however, its relationship with public environmental finance is largely ignored. In particular, a strand

10990836, 0, Downloaded from https://onlinelibrary.wiley.com/doi/10.1002/bse.71764 by NICE, National Institute for Health and Care Excellence, Wiley Online Library on [19/11/2026]. See the Terms and Conditions (https://onlinelibrary.wiley.com/terms-and-conditions) on Wiley Online Library for rules of use; OA articles are governed by the applicable Creative Commons License

of literature reports that SE is associated with weaker environmental performance because informal entities operate in the informal sector to avoid taxes, regulations, and environmental compliance, raising emissions and ecological footprint (Biswas et al. 2012; Dada et al. 2021; Baloch et al. 2022; Wang et al. 2024). Another strand reaches the opposite conclusion because SE is labor-intensive and capital-shallow, replacing pollutant production in the formal sector at the margin and thereby reducing aggregate emissions (Dada et al. 2023). This confrontation between these two findings is rare in the literature but substantially important. Also, it implies that SE affects environmental pressures as well as fiscal capacity that funds environmental protection.

As an institutional barrier to fiscal authorities, SE reduces government tax revenue, including environmental taxes (Biswas et al. 2012; Medina and Schneider 2018), and limits discretionary public spending (Wang et al. 2023; Guan et al. 2025; Wei et al. 2025; S. U. Rahman et al. 2025). Fiscal capacity theory supports this view, stating that the long-run ability of a government to fund public goods, including environmental policy, depends on the structural determinants of its fiscal base; however, SE is likely to reduce it (Besley et al. 2013). The existing literature has largely ignored the public environmental fiscal consequences of SE. Nguyen et al. (2026) demonstrates that environmental taxes may expand SE by increasing compliance costs for formal businesses.

The fiscal impacts of SE are distinct, not interchangeable. Environmental tax revenue, which is collected directly from official economic activities, is expected to be the most immediately exposed to the fiscal impact of SE (narrow tax base or tax base erosion). Public environmental expenditure is affected more indirectly through limited fiscal capacity and budgetary resources due to SE. Biodiversity expenditure is the most distinctive case and is therefore examined separately in the following subsection.

2.2 | SE and Biodiversity Expenditure

Biodiversity finance, although a subcomponent of public environmental expenditure in accounting terms, differs from other categories in important ways. Hanley and Barbier (2009) note that biodiversity is a public good whose provision is highly discretionary, weakly connected to immediate public interests, and especially exposed to fiscal compression during government budget allocation processes. OECD (2021) and Deutz et al. (2020) highlight the persistent under-financing of biodiversity programs, even in countries committed to the Kunming–Montreal Global Biodiversity Framework. In functional terms, and more importantly, biodiversity expenditure is predominantly remedial rather than preventive. It finances programs related to protected-area enforcement, habitat restoration, species recovery, and ecological monitoring, whereas environmental taxes seek to price environmentally harmful activities. Therefore, biodiversity expenditures are directed toward ecosystems whose degradation has already originated. This preventive–remedial distinction is critical, as it indicates that biodiversity expenditures are likely to be affected by the SE through fiscal and political prioritization channels, distinct from those affecting environmental tax revenue and public environmental expenditures.

The functional factor introduces a counterintuitive framework, which is against the fiscal-erosion channel. The causes of biodiversity loss are disproportionately related to informal activities (Nellemann et al. 2016; Sundström 2016), which do not contribute to environmental tax revenue but damage the ecological system, which requires public remedial expenditures for biodiversity protection. Therefore, a larger SE is associated with higher biodiversity expenditures and reduces public finance available for biodiversity protection. This creates an ex ante theoretical complexity about the impact of SE on biodiversity expenditures. On the one side, the fiscal erosion framework suggests that SE reduces fiscal capacity for environmental and biodiversity protection, but on the other side, it is associated with increased demand for restoration, conservation, and enforcement expenditures. Resolving this complexity empirically is the central theme of the study.

2.3 | The Role of FinTech in Formalization and Fiscal Capacity

A growing literature establishes that digitalization in the financial sector reduces SE. Syed et al. (2021) and S. U. Rahman et al. (2023) empirically find that FinTech development decreases SE across panel countries by drawing informal economic activities into the formal sector. Alkaseasbeh et al. (2023) and Bahar (2022) support their findings, whereas Feng et al. (2023) highlight that FinTech decreases shadow banking activities among nonfinancial firms. A parallel literature shows that FinTech strengthens green finance in private capital markets by facilitating sustainable investment, transparency, financial access, and market efficiency (Zhang et al. 2023; Chien et al. 2025; Babar and Wu 2025; Khan and Shahid 2025). These strands in the literature have largely developed separately. Studies highlight the FinTech-SE and FinTech-private green finance relationships; however, it is largely ignored whether FinTech plays a significant moderating role in investigating the impact of SE on public environmental and biodiversity finance.

According to the financial intermediation theory, increasing financial access raises the opportunity cost of operating in the informal sector at the firm level (Diamond 1984; Levine 1997). FinTech increases transparency in financial transactions through digital payments, mobile money, electronic wallets, and electronic invoicing, which creates a digital footprint that can be used for tax purposes even when the business operates partly informally (Aron 2018; Immordino and Russo 2018; Khera et al. 2022). Therefore, higher and better transaction traceability increases the loss associated with informality, which provides a foundation for examining the moderating role of FinTech in the SE and environmental public finance. The same infrastructure, however, extends commercial reach into previously inaccessible areas, including biodiversity-sensitive frontiers where digital credit and payment connectivity enable resource extraction and land conversion (Suri and Jack 2016), implying a distinct and countervailing direct effect on the remedial arm. The prediction is therefore asymmetric: FinTech relieves the revenue-side compression of the fiscal regime without symmetrically relieving its remedial-side expansion.

A methodological limitation applies to this moderation. Because higher fiscal capacity may itself facilitate FinTech

10990836, 0, Downloaded from https://onlinelibrary.wiley.com/doi/10.1002/bse.71764 by NICE, National Institute for Health and Care Excellence, Wiley Online Library on [19/11/2026]. See the Terms and Conditions (https://onlinelibrary.wiley.com/terms-and-conditions) on Wiley Online Library for rules of use; OA articles are governed by the applicable Creative Commons License

adoption, the FinTech–revenue association is potentially subject to reverse causality (a concern also relevant to the SE relationship considering Nguyen et al. 2026). The empirical strategy addresses this through dynamic estimation and directional testing, and this study explains the FinTech results as robust conditional associations rather than as clear causal effects.

2.4 | Machine Learning in Environmental and Fiscal Forecasting

A substantial literature distinguishes estimating causal inference from the estimation of forecasting, considering them as complementary rather than competing tasks (Mullainathan and Spiess 2017; Athey and Imbens 2019). Flexible algorithmic models often uncover nonlinear and interactive structures that linear specifications miss, and in environmental economics, they have been applied to forecast emissions, energy demand, and resource use (Storm et al. 2020; Magazzino et al. 2021). A consistent finding is that such models outperform linear benchmarks when the underlying process is structured but offer little advantage when outcomes are dominated by discretionary or idiosyncratic shocks. This pattern is useful here. If the three environmental fiscal outcomes differ in how much of their variation is structurally determined, the forecasting results will reveal it and will complement the econometric estimates rather than duplicate them.

The study employs two econometric techniques, including double machine learning (Chernozhukov et al. 2018) with a tensor representation and a graph-based learner (Kipf and Welling 2017), which is appropriate to the mutual predicament of revenue, expenditure, and SE, with feature selection, leakage, and control out-of-sample evaluation reported transparently. Importantly, the machine-learning analysis is used to assess predictive performance and structural regularity.

3 | Methodology

3.1 | Theoretical Framework

The study is based on three main frameworks, linking the SE to environmental fiscal capacity, which also facilitates global biodiversity by approximately 80% (BIOFIN 2024; Organisation for Economic Co-operation and Development 2020). According to Besley and Persson (2013), environmental policy is a public good, may be financed by government tax revenue; however, the SE reduces it by narrowing down the tax base, reducing environmental tax revenue, and undermining enforcement (S. U. Rahman et al. 2026; Dreher and Schneider 2010; Medina and Schneider 2018). Therefore, it predicts an adverse impact on environmental tax revenue and expenditure, which adjusts indirectly through fiscal constraints due to lower tax revenue.

Moreover, financial intermediation theory supports the critical role of FinTech, which fundamentally formalizes transactions (Diamond 1984; Levine 1997), rather than enterprises themselves. FinTech services, such as digital payments, mobile money platforms, and ATM transactions, produce a fiscal footprint even for unregistered economic activities (Aron 2018). In this way, FinTech is expected to reduce the adverse impact of SE on environmental tax revenue by enhancing transaction traceability and compliance and expanding the observable tax base (S. U. Rahman et al. 2023). However, the same infrastructure enhances commercial access to biodiversity-sensitive frontiers, indicating an adverse direct impact on biodiversity spending (Suri and Jack 2016; S. U. Rahman et al. 2026).

Furthermore, the Pollution Haven Hypothesis supports the discussion, arguing that SE is a within-country pollution haven sector, which also affects biodiversity due to illegal logging, mining, and extraction of natural resources (Copeland and Taylor 1994; Baksi and Bose 2016; S. U. Rahman et al. 2025). These activities impose real and accumulating ecological costs that the government is eventually required to address through biodiversity expenditure activities, such as protected area enforcement, habitat restoration, species recovery, and monitoring infrastructure. Also, SE rarely contributes to public revenue while increasing spending on environmental management and remedies (Brashares et al. 2014). Since biodiversity expenditures are mostly remedial rather than preventive (BIOFIN 2024), the SE is expected to increase them, contrary to its expected negative impact on preventive environmental fiscal instruments.

The integration of the above frameworks suggests an asymmetric relationship between SE and environmental fiscal capacity. On the one side, SE reduces the fiscal resources for environmental quality, but on the other side, it raises biodiversity expenditures. This creates a self-reinforcing, inefficient fiscal situation, as prevention is cheaper than remediation. This makes the current study distinct from the existing literature on emissions and pollution and provides a new framework, containing SE, environmental fiscal capacity, and biodiversity conservation public expenditures.

3.2 | Data and Variables

This study uses a balanced panel dataset for 24 OECD countries (list provided in Appendix A), from 2004 to 2022. The data period was selected based on data availability. The earliest data for FinTech are available from 2004, whereas for most variables, the latest data are available till 2022. The selected panel data are sufficient to capture multiple economic cycles, technological diffusion waves, the Paris Agreement (2015), and the Kunming–Montreal Global Biodiversity Framework (2022).

Environmental fiscal capacity is the government's tax collection from energy, transport, pollution, and resources, whereas public environmental expenditure measures governmental expenditures on environmental protection, which might be financed from green taxes (Organisation for Economic Co-operation and Development 2023). Biodiversity finance captures the government's expenditure explicitly allocated for biodiversity and habitat protection (Table 1).

The key independent variable, the SE, is sourced from F. Schneider's (2022) estimations for the OECD countries by

10990836, 0, Downloaded from https://onlinelibrary.wiley.com/doi/10.1002/bse.71764 by NICE, National Institute for Health and Care Excellence, Wiley Online Library on [19/11/2026]. See the Terms and Conditions (https://onlinelibrary.wiley.com/terms-and-conditions) on Wiley Online Library for rules of use; OA articles are governed by the applicable Creative Commons License

TABLE 1 | Variable definitions, measurement, and sources.

Variable	Proxy measure	Definition	Source
Public green or environmental finance (ER)	Environmental tax revenue	Environmental tax as % of GDP	OECD
Public environmental expenditure (EExp)	Public environmental expenditure	Government expenditure on environmental protection as % of GDP	OECD
Biodiversity finance (BIOEX)	Biodiversity expenditure	Public spending on biodiversity protection as % of GDP	OECD
Shadow economy (SE)	MIMIC	Size of informal economy as % of GDP	F. Schneider (2022)
FinTech (FinTech)	FinTech index	Composite index of the number of ATMS, credit cards, and debit cards	World Bank
SEFinTech	SE*FinTech	Interaction of SE and FinTech index to test the moderation hypothesis	Constructed
Economic growth	Log of GDP constant 2015	Natural logarithm of real GDP per capita (constant 2015 USD)	World Bank WDI

employing the Multiple Causes and Multiple Indicators (MIMIC) technique. The MIMIC approach is widely used in the literature, which measures the SE as a latent variable, using tax burden, regulatory burden, economic freedom, business freedom, unemployment rate, and GDP per capita as causes. By contrast, the official employment rate, GDP rate, and change in local currency per capita are used as indicators of SE.

FinTech is proxied by a digital-payment penetration index, constructed by principal component analysis (PCA) from three components, including ATM machines, credit cards, and debit cards, representing penetration of digital payment. Because digital penetration is particularly relevant for the study, it promotes transaction traceability and leaves records that expand formalization and reduce SE. Data for other indicators such as mobile money and digital bank users were rarely available for the OECD countries. Other FinTech proxies, such as platform lending, open banking, and neobank activities, represent financial innovations that are less likely to be related to formalization. Moreover, PCA explores the common variation across components and addresses potential multicollinearity concerns among them. The interaction term of SE*FinTech is the compound of SE and FinTech, measuring the moderating role of FinTech in the SE association with green finance and biodiversity finance.

Further, GDP growth (constant 2015) and institutional quality are included in the models to minimize omitted variable bias. Theoretically, economic growth (GDP growth) increases tax collection, which can influence both administrative and environmental spending (Grossman and Krueger 1995). Institutional quality comprises the World Governance Indicators, which control SE and environmental regulatory quality (F. G. Schneider 2002; Hussain and Dogan 2021).

3.3 | Economic Strategy

The empirical models for analyzing the impact of SE on environmental fiscal capacity are designed as follows:

$$Y_{it} = \alpha_{it} + \beta_1 SE_{it} + \beta_2 FinTech_{it} + \beta_3 IQ_{it} + \beta_4 GDP_{it} + \varepsilon_{it} \quad (1)$$

$$Y_{it} = \alpha_{it} + \beta_1 SE_{it} + \beta_2 FinTech_{it} + \beta_3 IQ_{it} + \beta_4 GDP_{it} + \beta_5 SE^{*} FinTech_{it} + \varepsilon_{it} \quad (2)$$

where Y_{it} represents one of the dependent variables for country i in year y, α is the intercept, and $\beta_{1.....}\beta_n$ is the slope or variation in the dependent variable due to the independent variable. SE is the shadow economy, *GDP* represents economic growth, *IQ* is institutional quality, and ε is the error term.

The methodological strategy with complementary estimation techniques is designed based on the characteristics. Each estimation technique addresses a distinct limitation of the related approach to ensure consistency in inferences. The OECD economies are strongly integrated through trade, capital flows, and institutional diffusion, indicating that a policy shock in one economy can be transmitted to other economies; hence, slope-homogeneous estimators may lead to biased estimations. Therefore, due to potential CSD in the panel, the study applies second-generation techniques. Moreover, environmental fiscal outcomes are persistent, and several regressors are potentially endogenous, suggesting applying one-step GMM to control for potential endogeneity. These estimation techniques are applied to identify and estimate the relationship between the variables and impose a linear-in-parameters structure; however, they are limited to quantifying how much of the variation in public environmental and biodiversity finance is explained by SE and FinTech, as opposed to arising from an idiosyncratic budgetary process. Accordingly, the study applies

10990836, 0, Downloaded from https://onlinelibrary.wiley.com/doi/10.1002/bse.71764 by NICE, National Institute for Health and Care Excellence, Wiley Online Library on [19/11/2026]. See the Terms and Conditions (https://onlinelibrary.wiley.com/terms-and-conditions) on Wiley Online Library for rules of use; OA articles are governed by the applicable Creative Commons License

machine learning techniques (Tensor Double and Graph-Inspired) to predict out-of-sample and higher order interactions.

3.3.1 | Pre-Estimation Diagnostics

To test CSD, the study employs the Pesaran (2004) CSD test. The null hypothesis of this approach assumes independence, and the statistics follow a standard normal distribution. Mathematically, it can be expressed as follows:

$$CSD = \sqrt{\frac{2T}{N(N-1)}\left(\sum_{i=1}^{N-1}\sum_{j=i+1}^{N}\hat{\rho}_{it}\right)} \tag{3}$$

Moreover, the Pesaran and Yamagata (2008) slope heterogeneity test (Δ and adjusted-Δ statistics) and its rejection support mean-group or common-correlated-effects estimators. This test offers both the standard and adjusted slope of heterogeneity, using the following mathematical equations.

$$\hat{\Delta}_{SH} = \sqrt{N(2K)^{-1}}\left(N^{-1}\hat{S} - K\right) \tag{4}$$

$$\hat{\Delta}_{ASH} = \sqrt{T + \frac{1}{2K(T-K-1)}}\left(N^{-1}\hat{S} - K\right) \tag{5}$$

Following CSD and heterogeneity, the study tests each series for stochastic nonstationarity by employing cross-sectionally augmented IPS (CIPS) and the cross-sectionally augmented Dickey–Fuller (CADF) test, proposed by Pesaran (2007). These tests extend the traditional Augmented Dickey–Fuller tests with cross-sectional averages at levels and first differences to consider common factors, confirming that the unit root outcomes are not biased by cross-sectional correlation.

Empirically, CADF can be stated as follows:

$$\Delta X_{it} = \beta_i + \pi_i x_{i,t-1} + \lambda_i \bar{x}_{t-1} + \delta_i \Delta\bar{x}_t + e_{it} \tag{6}$$

The addition of one lag led to Equation (8).

$$\Delta X_{it} = \beta_i + \pi_i x_{i,t-1} + \lambda_i \bar{x}_{t-1} + \sum_{j=0}^{P}\delta_i \Delta\bar{x}_{t-j} + \sum_{j=1}^{P}\varphi_{ij}\Delta x_{i,t-j} + e_{it} \tag{7}$$

where $\bar{x}_{t-1}$ indicates the cross-section and $\Delta x_{i,t-j}$ represents the mean of the lagged value at first difference. CIPS is mathematically presented as follows:

$$CIPS = N^{-1}\sum_{i=1}^{N} CADF_i \tag{8}$$

Further, Westerlund (2007) panel cointegration test is employed, which accounts for CSD and slope heterogeneity among the variables through bootstrap-based critical values. This test examines whether the error correction adjusted speed (α_i) is negative and significant with the panel statistics (P_t and P_a) and group statistics (G_t and G_a). The panel statistics test cointegration for the panel, whereas the group statistics test as a whole. At least one cointegrating unit confirms the cointegration between the dependent and independent variables and justifies direct estimation of long-run relationships. The panel and group statistics can be empirically estimated as follows;

$$P_T = \frac{\hat{a}}{se(\hat{a}_i)} \tag{9}$$

$$P_a = T\hat{a} \tag{10}$$

$$G_t = \frac{I}{N}\sum_{i=l}^{N}\frac{\hat{a}_i}{se(\hat{a}_i)} \tag{11}$$

$$G_a = \frac{I}{N}\sum_{i=l}^{N}\frac{T\hat{a}_i}{\hat{a}_i(1)} \tag{12}$$

3.3.2 | Common Correlated Effects (CCE) Estimation

To estimate the relationship among the variables, the study mainly applies CCEMG, proposed by Pesaran (2006). This technique is the primary estimation technique that addresses both CSD and slope heterogeneity, the two dominant features of the data (Eberhardt and Teal 2011). The baseline model for the CCEMG technique can be represented as follows:

$$Y_{it} = \alpha_i + \beta_i' X_{it} + \gamma_i' f_t + \epsilon_{it} \tag{13}$$

whereas Y_{it} is a dependent variable and X_{it} is the vector of regressors. β_i are the country-specific slopes, which consider slope heterogeneity; f_t represent unobserved common factors, with country-specific loadings γ_i, and ϵ_{it} is the idiosyncratic error. According to Pesaran (2006), cross-sectional averages $\bar{y}_t$ and $\bar{X}_t$ are consistent proxies for f_t, as $N \to \infty$, which yields the following:

$$Y_{it} = \alpha_i + \beta_i' X_{it} + c_i\bar{y}_t + d_i'\bar{X}_t + \epsilon_{it} \tag{14}$$

The country-specific slopes $\hat{\beta}_i$ are estimated by OLS, using Equation (14), which is then averaged as $\beta'_CCEMG = N^{-1}\sum_i \hat{\beta}_i$, with inference based on the nonparametric variance of the cross-country dispersion (Pesaran and Smith 1995).

3.3.3 | Robust Estimations

For robustness, the study employs complementary estimation techniques. A two-way fixed effects panel regression (with both country and year fixed effects) is estimated using Driscoll–Kraay standard errors, ensuring robustness for arbitrary forms of spatial and temporal dependence. Moreover, the one-step GMM is employed to address the potential endogeneity and dynamics in the panel. Environmental indicators are persistent, and SE and FinTech are potentially endogenous. Based on Arellano and Bover (1995) and Blundell and Bond (1998), this approach is designed to include a lagged dependent variable to consider instruments and endogenous regressors with their own lags, requiring no external instruments. Because CCEMG assumes weak exogeneity of regressors, this technique can directly identify whether the findings survive explicit treatment of dynamic endogeneity. The instrumental validity is assessed through the Sargan test, whereas Arellano–Bond tests (AR(1) and AR(2)) examine serial correlation.

10990836, 0, Downloaded from https://onlinelibrary.wiley.com/doi/10.1002/bse.71764 by NICE, National Institute for Health and Care Excellence, Wiley Online Library on [19/11/2026]. See the Terms and Conditions (https://onlinelibrary.wiley.com/terms-and-conditions) on Wiley Online Library for rules of use; OA articles are governed by the applicable Creative Commons License

TABLE 2 | Descriptive statistics.

Variable	Mean	Median	Max	Min	Std. dev.	Skewness	Kurtosis	J-B stat.	Prob.
lnBio	−2.891	−2.881	−1.145	−7.617	1.019	−1.139	5.326	200.480	0.000
lnEExp	−0.344	−0.305	0.554	−2.058	0.426	−0.455	3.546	21.286	0.000
lnFinTech	0.007	−0.382	3.941	−2.784	1.426	0.921	3.453	68.138	0.000
lnER	22.736	22.893	25.271	19.331	1.355	−0.186	2.429	8.777	0.012
lnGDP	26.414	26.576	29.153	23.624	1.420	−0.057	2.313	9.171	0.010
lnSE	2.698	2.714	3.456	1.705	0.427	−0.166	1.932	23.641	0.000
lnIQ	0.002	0.507	3.354	−6.232	2.262	−0.415	2.007	31.716	0.000

Note: All variables are in natural logarithms.
Abbreviations: *lnBio* = log biodiversity expenditure; *lnEExp* = log public environmental expenditure; *lnER* = log environmental tax revenue; *lnFT* = log FinTech index; *lnGDP* = log GDP per capita; *lnIQ* = log institutional quality; *lnSE* = log shadow economy.

3.3.4 | Dumitrescu–Hurlin Panel Causality Tests

To estimate the causal direction of the relationships and to examine the reverse causality between variables, the study employs the Dumitrescu and Hurlin (2012) panel causality test. Unlike Granger causality, which assumes homogeneity in slopes, this technique allows for heterogeneous regression coefficients, estimating the average Wald statistics across individual cross-sections for all pairs of the key variables. The *W*-bar statistics and the standardized *Z*-bar statistics test the null hypothesis of homogeneous noncausality. Employing a nonparametric bootstrap procedure ensures validity under CSD.

3.4 | Predictive Analysis: Purpose and Design

Econometric analysis explores and estimates long-run relationships among the variables; however, it does not identify how much of the variation in each environmental dynamic and biodiversity finance is structurally predictable as opposed to being governed by idiosyncratic budgetary processes. Therefore, prediction serves a distinct purpose and is kept conceptually separate from causal inference; however, no causal claim relies on forecasting analysis. Studies show that machine learning techniques for forecasting can outperform conventional techniques when the underlying process is structured but provide little advantage when variations are dominated by discretionary or unobserved shocks (Mullainathan and Spiess 2017; Athey and Imbens 2019). If the preventive fiscal instruments exhibit stronger out-of-sample predictability than the discretionary remedial instrument, the predictive evidence independently corroborates the structural hierarchy implied in the study. Thus, the predictive analyses are complementary, rather than substitutes for econometric analysis.

Accordingly, the study applies two artificial-intelligence frameworks (Tensor-DML and Graph-ML) to forecast the three econometric models. The Tensor-DML framework combines deep tensor representation learning with the orthogonalization mechanism of double machine learning. It is designed to capture nonlinear, multidimensional, and heterogeneous relationships while minimizing the estimation bias induced by high-dimensional confounding. The framework operates in two stages. In the first, the nuisance parameters associated with the explanatory variables are estimated through tensor-based neural representations; in the second, orthogonal residual learning isolates the unbiased predictive effect. An advantage of Tensor-DML is the ability to process high-dimensional economic data, limit overfitting, model nonlinear dependencies, and improve forecasting accuracy. The Graph-ML paradigm represents the economic system as a graph in which variables are nodes and their interdependencies are edges.

The predictor set comprises SE, institutional quality, gross domestic product (lnGDP), and FinTech.

For each dependent variable, two specifications are estimated: a base model containing direct effects only and an interaction model admitting nonlinear interaction effects among the predictors. The general forecasting relationship is as follows:

$$Y_t = f\left(lnSE_t, lnGDP_t, lnIQ_t\ lnFinTech_t\right) + \varepsilon_t \tag{15}$$

where Y_t denotes lnER, lnEEXP, or lnBIOEX at time t, and ε_t is the stochastic error term.

Predictive performance of the models is evaluated by RMSE, MAE, and out-of-sample R^2. The Diebold–Mariano test is used to examine whether the differences in forecasting accuracy between competing models are statistically significant.

The forecasting structure can be described as follows:

$$Y_t = \theta D_t + g\left(X_t\right) + u_t \tag{16}$$

where D_t is the target predictive component, X_t the control vector, $g\ (X_t)$ the nonlinear nuisance function captured through tensor representations, and u_t the disturbance. Orthogonal residuals are formed as follows:

$$\tilde{Y}_t = Y_t - \hat{g}\left(X_t\right), \tilde{D}_t = D_t - \hat{m}\left(X_t\right) \tag{17}$$

where $\hat{g}\ (X_t)$ and $\hat{m}(X_t)$ are machine-learning estimates of the nuisance functions, and the parameter of interest is recovered from

$$\hat{\theta} = arg\ min\theta\ \Sigma_{t=1}^{T}\left(\tilde{Y}_t - \theta\ \tilde{D}_t\right)^2 \tag{18}$$

10990836, 0, Downloaded from https://onlinelibrary.wiley.com/doi/10.1002/bse.71764 by NICE, National Institute for Health and Care Excellence, Wiley Online Library on [19/11/2026]. See the Terms and Conditions (https://onlinelibrary.wiley.com/terms-and-conditions) on Wiley Online Library for rules of use; OA articles are governed by the applicable Creative Commons License

TABLE 3 | Pairwise correlation matrix and CD test.

Variable	*lnER*	*lnEExp*	*lnBio*	*lnSE*	*lnFT*	*lnIQ*	*lnGDP*	CSD Stat.
lnER	**1.000**							32.306***
lnEExp	0.129	**1.000**						4.339***
lnBio	−0.058	0.094	**1.000**					0.761***
lnSE	−0.422	0.068	−0.077	**1.000**				61.863***
lnFT	0.830	0.249	−0.144	−0.368	**1.000**			12.079***
lnIQ	0.208	−0.279	0.246	−0.716	0.107	**1.000**		4.770***
lnGDP	0.972	0.127	−0.062	−0.487	0.873	0.245	**1.000**	51.383***

Note: Lower triangle reports Pearson pairwise correlations. The final column reports the Pesaran (2004) CD test statistics for each variable.
*** denotes rejection of the null of cross-sectional independence at the 1% level.

TABLE 4 | Slope heterogeneity test.

Model specification	Δ Statistic	Δ Adj. statistic
$lnER = f(lnSE, lnFinTech, lnIQ, lnGDP)$	13.313***	16.095***
$lnEExp = f(lnSE, lnFinTech, lnIQ, lnGDP)$	10.172***	12.297***
$lnBio = f(lnSE, lnFinTech, lnIQ, lnGDP)$	9.159***	11.072***
$lnER = f(lnSE, lnFinTech, lnSE*FinTech, lnIQ, lnGDP)$	11.254***	14.161***
$lnEExp = f(lnSE, lnFinTech, lnSE*FinTech, lnIQ, lnGDP)$	8.669***	10.909***
$lnBio = f(lnSE, lnFinTech, lnSE*FinTech, lnIQ, lnGDP)$	7.551***	9.502***

Note: Δ and Δ denote the standard and bias-adjusted slope heterogeneity statistics of Pesaran and Yamagata (2008).
***$p < 0.01$.

4 | Results and Discussion

4.1 | Preliminary Diagnostics

Table 2 reports the descriptive statistics. The mean for biodiversity finance, environmental tax revenue, and public environmental finance is −2.891, −0.344, and 22.736, respectively, with corresponding standard deviations of 1.019, 0.426, and 1.355. Biodiversity finance exhibits high kurtosis with 5.326 and strong negative skewness (−1.139), showing a leptokurtic and left-skewed distribution. The significant Jarque-Bera estimations suggest rejection of normality for all variables. The SE ranges from 1.07 to 3.456 with a mean of 2.698, suggesting heterogeneity in informality in the cross-country panels, in line with the SE estimates of Medina and Schneider (2019) and Elgin et al. (2021).

Table 3 reports the pairwise correlations and the Pesaran (2004) CD test. The SE is negatively associated with environmental tax revenue (public environmental finance), FinTech, and institutional quality. The CD test rejects cross-sectional independence at the 1% level, confirming a strong interdependence among OECD countries through macroeconomic indicators and their shared exposure to global shocks (Awosusi et al. 2022).

The Pesaran and Yamagata (2008) test results in Table 4 reject slope homogeneity, as both standard and bias-adjusted statistics are significant at 1%, indicating the presence of heterogeneity across all models. Westerlund (2007) cointegration test (Table 5) rejects the null hypothesis of no cointegration, confirming the presence of a long-run relationship. Together, these tests suggest using the CCEMGs as a primary estimator, with both one-step GMM and Driscoll–Kraay fixed effects used as robustness checks.

4.2 | Long-Run Relationship Estimations

4.2.1 | The SE and Environmental Tax Revenue

Following the preliminary test, the study estimates the coefficients of long-run relationships, as presented in Table 6. The results indicate that SE consistently reduces environmental tax revenue, as a 1% increase in SE is associated with a decrease in environmental tax revenue by 1.248%, supported by Driscoll–Kraay fixed-effect and one-step GMM (Table 7) estimations. However, the magnitude of coefficients varies across estimators, but the sign and significance are consistent, and the association is considerably stronger for environmental tax revenue than for environmental expenditures. This suggests that environmental tax revenue is directly and more exposed to informality, as it is mainly levied on official or recorded economic activities. Environmental taxes such as fossil fuel taxes, carbon taxes, pollution taxes, and resource extraction taxes need registration and reporting infrastructure (Biswas et al. 2012; Elgin and Oztunali 2014). Informal activities often overlook regulations, including environmental regulatory frameworks, through which these instruments are taxed. Informal manufacturing activities are usually excluded from official emissions inventories, unregistered transport often avoids fuel-tax monitoring systems, and resource-extracting enterprises generally operate outside regulatory frameworks. The fragmented, small-scale, and geographically dispersed nature of informal firms also raises the administrative cost of tax enforcement relative to the revenue

10990836, 0, Downloaded from https://onlinelibrary.wiley.com/doi/10.1002/bse.71764 by NICE, National Institute for Health and Care Excellence, Wiley Online Library on [19/11/2026]. See the Terms and Conditions (https://onlinelibrary.wiley.com/terms-and-conditions) on Wiley Online Library for rules of use; OA articles are governed by the applicable Creative Commons License

TABLE 5 | Panel cointegration tests.

Model	Stat	Value	*Z*-value	*p*	Robust *p*
$lnER = f(lnSE, lnFinTech, lnIQ, lnGDP)$	Gt	−2.296***	1.509	0.066	0.000
	Ga	−6.910***	2.045	0.980	0.000
	Pt	−8.716***	0.628	0.265	0.000
	Pa	−5.656***	0.307	0.621	0.000
$lnEExp = f(lnSE, lnFinTech, lnIQ, lnGDP)$	Gt	−2.776***	3.797	0.000	0.000
	Ga	−5.932***	2.719	0.997	0.000
	Pt	−12.514***	3.626	0.000	0.000
	Pa	−6.165***	0.034	0.486	0.000
$lnBio = f(lnSE, lnFinTech, lnIQ, lnGDP)$	Gt	−3.051***	5.107	0.000	0.000
	Ga	−6.672***	2.209	0.986	0.000
	Pt	−18.375**	8.252	0.000	0.050
	Pa	−7.686	1.053	0.146	0.100
$lnER = f(lnSE, lnFinTech, lnSE*FinTech, lnIQ, lnGDP)$	Gt	−2.288*	0.429	0.334	0.080
	Ga	−5.628*	3.889	1.000	0.080
	Pt	−9.178	0.032	0.513	0.200
	Pa	−4.872	1.947	0.974	0.160
$lnEExp = f(lnSE, lnFinTech, lnSE*FinTech, lnIQ, lnGDP)$	Gt	−2.340**	0.682	0.248	0.040
	Ga	−3.898	4.993	1.000	0.520
	Pt	−11.437*	1.816	0.035	0.060
	Pa	−4.008	2.479	0.993	0.400
$lnBio = f(lnSE, lnFinTech, lnSE*FinTech, lnIQ, lnGDP)$	Gt	−2.959***	3.664	0.000	0.000
	Ga	−5.073	4.244	1.000	0.100
	Pt	−16.520**	5.975	0.000	0.033
	Pa	−5.340*	1.658	0.951	0.067

Note: Gt and Ga are group-mean statistics; Pt and Pa are panel statistics. Robust *p*-values are based on bootstrap replications controlling for cross-sectional dependence. Null hypothesis: no cointegration.
***$p < 0.01$.
**$p < 0.05$.
*$p < 0.10$.

likely to be collected (Markandya et al. 2013). Therefore, the SE reduces the environmental taxes in two ways: by shifting economic activities beyond formal regulations and by weakening tax compliance incentives among marginally formal firms that face a competitive disadvantage from unregulated firms (Blackburn et al. 2012).

This finding contributes to the literature on informality and environmental policy, which finds that SE is associated with higher carbon emissions and ecological footprint (Baloch et al. 2022; Dada et al. 2023). It complements the findings of S. U. Rahman et al. (2025), which state that SE affects consumption-based carbon emissions and biodiversity in the G7 countries, but does not separately explore its impact on environmental revenue. Therefore, the present finding addresses an important gap in the SE–environmental degradation association.

4.2.2 | The SE and Public Environmental Expenditure

The SE impact on public environmental expenditures is negative and significant across all estimators (CCEMG, one-step GMM, and Driscoll–Kraay). A 1% increase in SE reduces public environmental expenditure by 0.964% under CCEMG and is consistently negative in the other two estimators. This finding is not surprising; rather, it is theoretically grounded in public economics. The primary mechanism for the negative impact of SE on reducing environmental expenditure is a budget-constraint channel.

Public environmental expenditures are often discretionary, rather than mandatory, making them more vulnerable to budgetary reductions during reduced tax revenue collection. In the political economy of fiscal adjustment, the government tends

10990836, 0, Downloaded from https://onlinelibrary.wiley.com/doi/10.1002/bse.71764 by NICE, National Institute for Health and Care Excellence, Wiley Online Library on [19/11/2026]. See the Terms and Conditions (https://onlinelibrary.wiley.com/terms-and-conditions) on Wiley Online Library for rules of use; OA articles are governed by the applicable Creative Commons License

TABLE 6 | Results: CCEMG and Driscoll–Kraay fixed effects.

Common correlated effects mean group (CCEMG)			
Variable	***lnER***	***lnEExp***	***lnBio***
Without the interaction term			
lnSE	−1.248*** (0.405)	−0.964* (0.565)	−1.181** (0.613)
lnFinTech	0.523*** (0.160)	0.337* (0.178)	−0.964** (0.506)
lnIQ	0.087* (0.046)	0.017 (0.046)	−0.024 (0.245)
lnGDP	−0.768** (0.326)	−0.731* (0.420)	0.317 (1.332)
With the interaction term (*lnSE*FinTech*)			
lnSE	−1.167*** (0.309)	−0.663* (0.352)	2.142* (1.130)
lnFinTech	0.309** (0.130)	−1.814** (2.605)	−1.441* (0.816)
*lnSE*FinTech*	0.100*** (0.057)	1.880** (0.869)	−2.988* (1.767)
lnIQ	−0.071 (0.064)	−0.079 (0.054)	0.540 (0.439)
lnGDP	0.119 (0.321)	0.545 (1.065)	1.938 (3.578)
Driscoll–Kraay fixed effects			
Variable	***lnER***	***lnEExp***	***lnBio***
Without the interaction term			
lnSE	−0.46*** (0.115)	−0.215*** (0.074)	−0.018*** (0.008)
lnFinTech	0.22*** (0.070)	0.066* (0.042)	−0.01* (0.004)
lnIQ	0.019* (0.009)	−0.065*** (0.016)	−0.054 (0.033)
lnGDP	0.198 (0.150)	−0.679*** (0.112)	−1.47** (1.685)
Sargan–Hansen	24.531***	12.720**	7.059*
With the interaction term (*lnSE*FinTech*)			
lnSE	0.349*** (0.082)	−0.539* (0.131)	−0.191** (0.085)
lnFinTech	0.070* (0.038)	−0.529*** (0.078)	0.303** (0.130)
*lnSE*FinTech*	0.029** (0.011)	0.001 (0.006)	−0.059*** (0.016)
lnIQ	−0.052 (0.061)	0.025 (0.115)	−0.624*** (0.123)
lnGDP	−0.527** (0.219)	0.277*** (0.035)	−0.088 (0.058)
Sargan–Hansen	27.442***	12.648**	12.187**

Note: Coefficients reported standard errors in parentheses. All models include country fixed effects and cross-sectional averages (CCEMG) or year fixed effects (DK-FE).
***$p < 0.01$.
**$p < 0.05$.
*$p < 0.10$.

to prioritize the preservation of mandatory expenditure while compromising on environmental and R&D budget allocations (López et al. 2011; Halkos and Paizanos 2013).

This outcome further reinforces the fiscal one. Large SE is associated with weaker administrative and monitoring capacity (Dreher et al. 2009), so that even where nominal expenditure is allocated, its effectiveness is diminished. By identifying the SE as a structural rather than merely cyclical determinant of environmental fiscal stress, the study explains why environmental fiscal capacity remains persistently constrained in economies with substantial SE.

4.2.3 | The SE and Biodiversity Expenditures

The SE is negatively and statistically significant on biodiversity finance (expenditure) across all estimators. Specifically, a 1% increase in SE reduces biodiversity finance by 1.181% (under CCEMG), supported by one-step GMM and Driscoll–Kraay estimations. This outcome is coherent and complements the SE-green finance findings that the SE systematically reduces environmental tax revenue, public spending on environmental protection, and biodiversity-targeted expenditures. This indicates that SE not only affects green finance dimensions but also weakens the entire ecology of environmental policy financing. This

10990836, 0, Downloaded from https://onlinelibrary.wiley.com/doi/10.1002/bse.71764 by NICE, National Institute for Health and Care Excellence, Wiley Online Library on [19/11/2026]. See the Terms and Conditions (https://onlinelibrary.wiley.com/terms-and-conditions) on Wiley Online Library for rules of use; OA articles are governed by the applicable Creative Commons License

TABLE 7 | One-step system GMM estimates with instrument diagnostics.

Variable	*lnER*	*lnEExp*	*lnBio*
Without interaction term			
lnSE	−0.568***	−1.251**	−0.884**
	(0.157)	(0.540)	(0.373)
lnFinTech	0.381***	0.006*	−1.994***
	(0.020)	(0.086)	(0.278)
lnIQ	0.058***	−0.159***	−0.590***
	(0.012)	(0.052)	(0.091)
lnGDP	0.652***	0.008	1.530***
	(0.018)	(0.087)	(0.285)
No. of instruments	31	30	32
No. of groups (*N*)	24	24	24
AR(1) *p*-value	0.024	0.000	0.098
AR(2) *p*-value	0.267	0.744	0.983
Sargan *p*-value	0.000	0.000	0.000
With interaction term (*lnSE*FinTech*)			
lnSE	−0.278***	−0.424*	−0.495*
	(0.090)	(0.238)	(0.276)
lnFinTech	0.049*	1.342***	−0.538*
	(0.040)	(0.127)	(0.508)
*lnSE*FinTech*	−0.034***	−0.500***	−0.029*
	(0.011)	(0.055)	(0.157)
lnIQ	−0.033***	0.059***	−0.106*
	(0.012)	(0.022)	(0.063)
lnGDP	0.035	0.115***	0.308
	(0.025)	(0.041)	(0.207)
No. of instruments	34	32	35
No. of groups (*N*)	24	24	24
AR(1) *p*-value	0.000	0.074	0.002
AR(2) *p*-value	0.163	0.12	0.346
Sargan *p*-value	0.039	0.000	0.000

Note: Standard errors in parentheses. The instrument set is collapsed following Roodman (2009), and the lag range is restricted to lag(2 3) for the lnER and lnBio equations and lag(1 2) for the lnEExp equations, holding the instrument count at or below the number of cross-sectional units in every specification. AR(1) and AR(2) are the Arellano–Bond tests for first- and second-order serial correlation in the first-differenced residuals.
***$p < 0.01$.
**$p < 0.05$.
*$p < 0.10$.

finding combines the budget-constraint channel with the regulatory enforcement framework. Biodiversity expenditure funds protected-area management, anti-poaching enforcement, habitat restoration programs, and species-conservation monitoring, which not only require fiscal allocations but also the institutional and administrative capacity to deploy fiscal resources effectively in remote areas. The same institutional weaknesses that sustain informality also undermine the effectiveness of conservation institutions (Dreher et al. 2009; Sundström 2016). As a result, this motivates the government to reduce budget allocation for biodiversity protection due to lower expected return per unit of expenditure. In line with this dynamic, Sundström (2016) noticed a linear association between higher levels of corruption, informality, and biodiversity loss. The result is a structural asymmetry between the ecological pressure that informality generates and the fiscal capacity available to counter it.

10990836, 0, Downloaded from https://onlinelibrary.wiley.com/doi/10.1002/bse.71764 by NICE, National Institute for Health and Care Excellence, Wiley Online Library on [19/11/2026]. See the Terms and Conditions (https://onlinelibrary.wiley.com/terms-and-conditions) on Wiley Online Library for rules of use; OA articles are governed by the applicable Creative Commons License

It is worth noting that the direction of this relationship is theoretically nontrivial. SE erodes the government's revenue tax base, which, as a result, reduces the allocation for discretionary public spending, weakens institutional and administrative capacity for implementing environmental programs effectively, and changes political equilibrium in favor of resource extraction rather than the protection and conservation of natural resources.

4.2.4 | The Role of FinTech (Direct Effects and the Moderation of SE)

The coefficients of FinTech on both environmental tax revenue and expenditures in the baseline models are positive and statistically significant across all estimations. These findings are theoretically convincing and empirically consistent with the transaction-formalization mechanism, where expanding digital payments reduces informality by improving transaction monitoring, detection, and enforcement capabilities. As a result, it expands the observable tax base by which environmental taxes and other related fiscal instruments can be implemented (Khera et al. 2022; Ozili 2018; Qin et al. 2024). In this way, FinTech improves fiscal capacity and promotes the government's ability to mobilize environmental revenues, thereby supporting environmental initiatives. These outcomes are consistent with earlier studies (Cheng et al. 2023), highlighting that FinTech adoption improves tax compliance, reduces informality, and increases revenue mobilization.

In contrast, the coefficient on FinTech in the biodiversity-expenditure equation is negative and statistically significant across all estimators. The sign is the opposite of the revenue effect, and its interpretation must follow the sign of the coefficient: A negative coefficient denotes lower biodiversity expenditure, not improved biodiversity protection. This pattern is consistent with a frontier-expansion mechanism rather than the formalization mechanism that operates on the revenue side. As digital credit and payment infrastructure extends into previously underserved areas, it lowers the transaction costs of commercial activity at the biodiversity frontier, including small-scale commercial agriculture, informal transport, mining, and resource extraction along forest edges and fishery zones (Nellemann et al. 2016; Suri and Jack 2016). Two channels can then depress recorded biodiversity expenditure: Financial digitalization may substitute private commercial development for public conservation activity in these areas, and by accelerating frontier commercialization, it raises the cost of effective conservation, lowering the expected return per unit of biodiversity spending. Under either channel, the negative sign is coherent, establishing the asymmetric role of FinTech: It supports the revenue arm of environmental fiscal capacity while exerting a countervailing downward pressure on the biodiversity arm.

The interaction term (*lnSE*FinTech*) tests whether digitalization decreases the fiscal effect of informality. The negative effect of the SE on environmental tax revenue is smaller where digital-payment penetration is higher, consistent with the view that FinTech draws informal activities into the formal sector. This outcome aligns with Qin et al. (2024), who find that digital finance moderates the fiscal externalities of informality, and that addressing informality can enhance the effectiveness of environmental fiscal instruments by expanding the tax base (Markandya et al. 2013). The interaction is, however, less robust than the direct effects and varies across estimators; it is therefore interpreted as directional evidence for the moderation hypothesis rather than as a precisely estimated parameter, and even where positive, it reduces rather than reverses the negative association between informality and environmental revenue.

4.2.5 | Robustness and Instrument Diagnostics

The convergence of three estimators with different identifying assumptions, CCEMG (robust to CSD and slope heterogeneity), Driscoll–Kraay (robust to spatial and serial correlation), and one-step GMM (addressing dynamic endogeneity) provides the basis for the study's robustness. The direct-effect signs are stable across all three estimators for every core relationship, which is a demanding robustness standard.

Diagnostic tests are reported alongside the estimates in Tables 6 and 7. For the one-step system GMM estimations, instrument proliferation is controlled by collapsing the instrument set following Roodman (2009) and by restricting the lag range used to construct the instruments so that the instrument count ranges from 30 to 35 across specifications and remains of the same order as the number of cross-sectional units ($N = 24$). The Arellano–Bond test indicates first-order serial correlation (AR(1) significant), as expected, whereas the AR(2) test finds no evidence of second-order serial correlation in all models, supporting the validity of the lagged instruments. The Sargan test of overidentifying restrictions rejects its null in most specifications; this is a recognized feature of the test in short panels, where it tends to over-reject and loses reliability. Accordingly, the one-step GMM results are treated as a supplementary dynamic robustness check rather than as the primary specification: Their value lies in confirming that the sign and significance of SE and FinTech coefficients obtained under the CCEMG and Driscoll–Kraay estimators are preserved once dynamic endogeneity is explicitly addressed. For the Driscoll–Kraay fixed-effects estimations, the reported Sargan–Hansen statistics (Table 6) are statistically significant, and inference is based on standard errors robust to cross-sectional and serial dependence.

4.3 | Forecasting Analysis

The above econometric estimations explain the direction and magnitude of the long-run relationships. However, the machine learning techniques address a distinct question: Quantifying how much variation in each fiscal outcome can be systematically recovered out-of-sample from informality, income, and financial digitalization. Therefore, the role of these two approaches is distinct, but corroborative. If the predictive hierarchy across the three outcomes matches the structural hierarchy obtained econometrically, the convergence provides independent, methodologically distinct support for the research main finding.

10990836, 0, Downloaded from https://onlinelibrary.wiley.com/doi/10.1002/bse.71764 by NICE, National Institute for Health and Care Excellence, Wiley Online Library on [19/11/2026]. See the Terms and Conditions (https://onlinelibrary.wiley.com/terms-and-conditions) on Wiley Online Library for rules of use; OA articles are governed by the applicable Creative Commons License

Tables 8 and 9 present the performance of the Tensor-DML and Graph-ML frameworks, respectively; Table 10 ranks all 12 model–specification combinations; Table 11 identifies the best models; and Table 12 reports the Diebold–Mariano tests of equal predictive accuracy. Environmental tax revenue is strongly forecastable (Tensor-DML out-of-sample R^2 of approximately 0.82; Graph-ML approximately 0.81). Public environmental expenditure is moderately forecastable under the better performing Tensor-DML base model (R^2 approximately 0.49) but poorly under Graph-ML. Biodiversity expenditure is not forecastable by either framework, with large errors or negative out-of-sample R^2, indicating that neither model out-predicts the historical mean. In every case, the addition of interaction terms fails to improve and often worsens predictive accuracy, indicating that the predictive content lies in the direct effects rather than in nonlinear interactions. Tensor-DML dominates Graph-ML overall, and the Diebold–Mariano tests (Table 12) confirm that this dominance is statistically significant for the expenditure and biodiversity outcomes, whereas the two frameworks are statistically indistinguishable for revenue, suggesting that the predictive structure is nonlinear rather than primarily relational.

TABLE 8 | Tensor-DML forecast performance.

Model	RMSE	MAE	R^2
lnER base model	0.4154	0.3637	0.8207
lnEEXP base model	0.1897	0.1573	0.4868
lnBIOEX base model	0.8622	0.7725	−1.2705
lnER interaction model	0.4141	0.3262	0.8219
lnEEXP interaction model	0.2434	0.2003	0.1554
lnBIOEX interaction model	0.8435	0.7421	−1.1732

Note: Forecast performance of the tensor double machine learning model. Abbreviations: lnBIOEX = log biodiversity expenditure; lnEEXP = log environmental expenditure; lnER = log environmental tax revenue; MAE = mean absolute error; R^2 = out-of-sample coefficient of determination; RMSE = root mean squared error.

TABLE 9 | Graph-inspired machine learning forecast performance.

Model	RMSE	MAE	R^2
lnER base	0.4322	0.3320	0.8060
lnEEXP base	0.2702	0.2132	−0.0409
lnBIOEX base	0.9492	0.8319	−1.7518
lnER interaction	0.4496	0.3782	0.7900
lnEEXP interaction	0.2606	0.2056	0.0312
lnBIOEX interaction	0.9935	0.8651	−2.0146

Note: Forecast performance of the graph-inspired machine learning model. Variable and metric definitions as in Table 8.

A negative out-of-sample R^2 for biodiversity finance suggests that the predictors employed do not forecast biodiversity finance better than its historical mean, but several features of the series could generate this result independently of any deeper structural signal. The economic content of the predictive hierarchy is, however, substantive. For policy, environmental revenue can be secured and improved through structural instruments that broaden the formal, digitally documented tax base, whereas biodiversity finance cannot be secured by those same levers alone and requires dedicated, ring-fenced, and better measured funding mechanisms if it is to be insulated from discretionary compression.

Figures 1, 2, and 3 reinforce these conclusions. The RMSE map shows consistently lower error dispersion for Tensor-DML on lnEEXP and lnER; the R^2 map shows strong explanatory power for the lnER models and near-zero or negative performance for lnEEXP and lnBIOEX under Graph-ML; and the combined map

TABLE 10 | Forecast comparison and ranking.

Framework	Model	RMSE	MAE	R^2	RMSE rank	MAE rank	R^2 rank	Overall score
Tensor-DML	lnEEXP base	0.190	0.157	0.487	1	1	5	7
Tensor-DML	lnEEXP interaction	0.243	0.200	0.155	2	2	6	10
Tensor-DML	lnER interaction	0.414	0.326	0.822	5	5	1	11
Graph-ML	lnEEXP interaction	0.261	0.206	0.031	3	3	7	13
Tensor-DML	lnER base	0.415	0.364	0.821	6	7	2	15
Graph-ML	lnER base	0.432	0.332	0.806	7	6	3	16
Graph-ML	lnEEXP base	0.270	0.213	−0.041	4	4	8	16
Graph-ML	lnER interaction	0.450	0.378	0.790	8	8	4	20
Tensor-DML	lnBIOEX interaction	0.844	0.742	−1.173	9	9	9	27
Tensor-DML	lnBIOEX base	0.862	0.772	−1.271	10	10	10	30
Graph-ML	lnBIOEX base	0.949	0.832	−1.752	11	11	11	33
Graph-ML	lnBIOEX interaction	0.993	0.865	−2.015	12	12	12	36

Note: Models are ranked separately on RMSE, MAE, and R^2 (1 = best). The overall score is the sum of the three ranks; a lower score denotes superior overall performance.

10990836, 0, Downloaded from https://onlinelibrary.wiley.com/doi/10.1002/bse.71764 by NICE, National Institute for Health and Care Excellence, Wiley Online Library on [19/11/2026]. See the Terms and Conditions (https://onlinelibrary.wiley.com/terms-and-conditions) on Wiley Online Library for rules of use; OA articles are governed by the applicable Creative Commons License

TABLE 11 | Best forecasting model by criterion.

Criterion	Framework	Model	RMSE	MAE	R^2
Best RMSE	Tensor-DML	lnEEXP base model	0.190	0.157	0.487
Best R^2	Tensor-DML	lnER interaction model	0.414	0.326	0.822

TABLE 12 | Diebold–Mariano tests of equal predictive accuracy (Tensor-DML vs. Graph-ML).

Tensor-DML model	Graph-ML model	DM stat.	p	Interpretation
lnER base	lnER base	−0.627	0.532	Not significant
lnEEXP base	lnEEXP base	−5.491	<0.001	1%***
lnBIOEX base	lnBIOEX base	−4.024	<0.001	1%***
lnER interaction	lnER interaction	−1.683	0.096	10%*
lnEEXP interaction	lnEEXP interaction	−1.177	0.242	Not significant
lnBIOEX interaction	lnBIOEX interaction	−3.958	<0.001	1%***

Note: The Diebold–Mariano statistic tests the null of equal out-of-sample predictive accuracy. A significant negative statistic indicates that the Tensor-DML forecast loss is significantly lower than that of Graph-ML.
*** and * denote significance at the 1% and 10% levels.

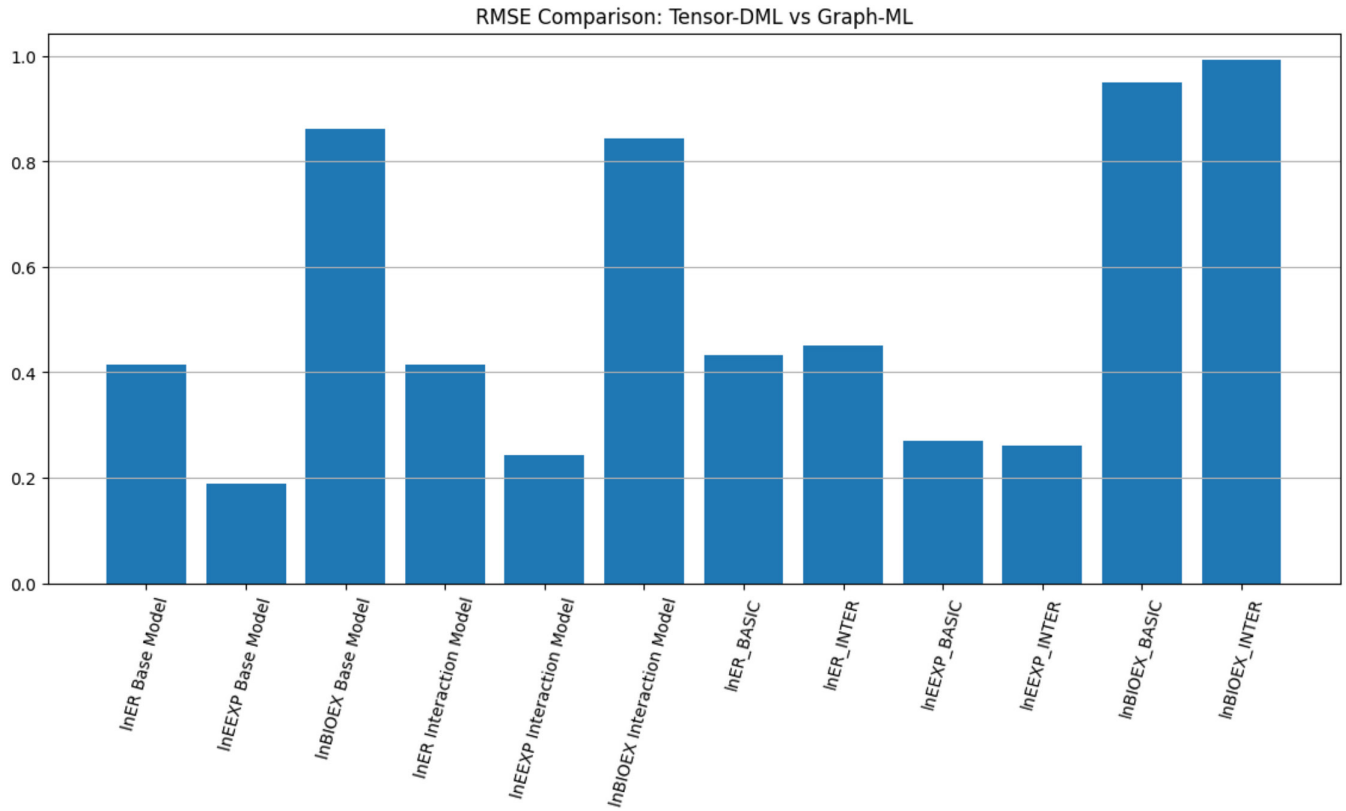


FIGURE 1 | RMSE comparison (Tensor-DML vs. Graph-ML). *Note:* Root mean squared error across all 12 model–specification combinations; lower bars indicate better accuracy.

shows the Tensor-DML combinations dominating across the performance space.

The Diebold–Mariano tests confirm the ranking. The forecast differences favor Tensor-DML decisively for environmental (lnEEXP base: DM = −5.491, $p < 0.001$) and for biodiversity expenditure (both specifications significant at 1%), even though the biodiversity models are weak in absolute terms. For environmental tax revenue, the two frameworks are statistically indistinguishable in the base specification ($p = 0.532$) and only weakly different in the interaction specification ($p = 0.096$), indicating broadly comparable accuracy when only direct effects are

10990836, 0, Downloaded from https://onlinelibrary.wiley.com/doi/10.1002/bse.71764 by NICE, National Institute for Health and Care Excellence, Wiley Online Library on [19/11/2026]. See the Terms and Conditions (https://onlinelibrary.wiley.com/terms-and-conditions) on Wiley Online Library for rules of use; OA articles are governed by the applicable Creative Commons License

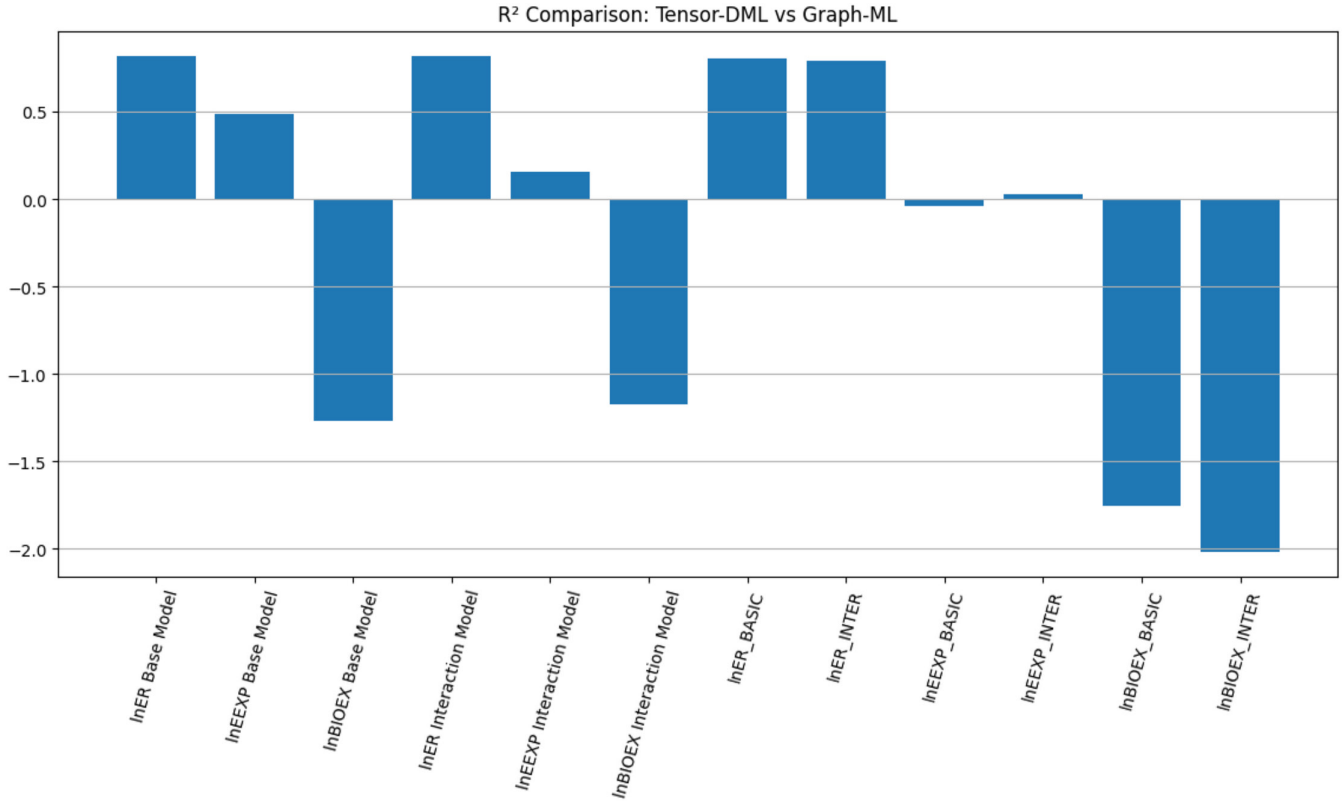


FIGURE 2 | R^2 comparison (Tensor-DML vs. Graph-ML). *Note:* Out-of-sample R^2 across all combinations; negative values indicate performance inferior to a historical-mean benchmark.

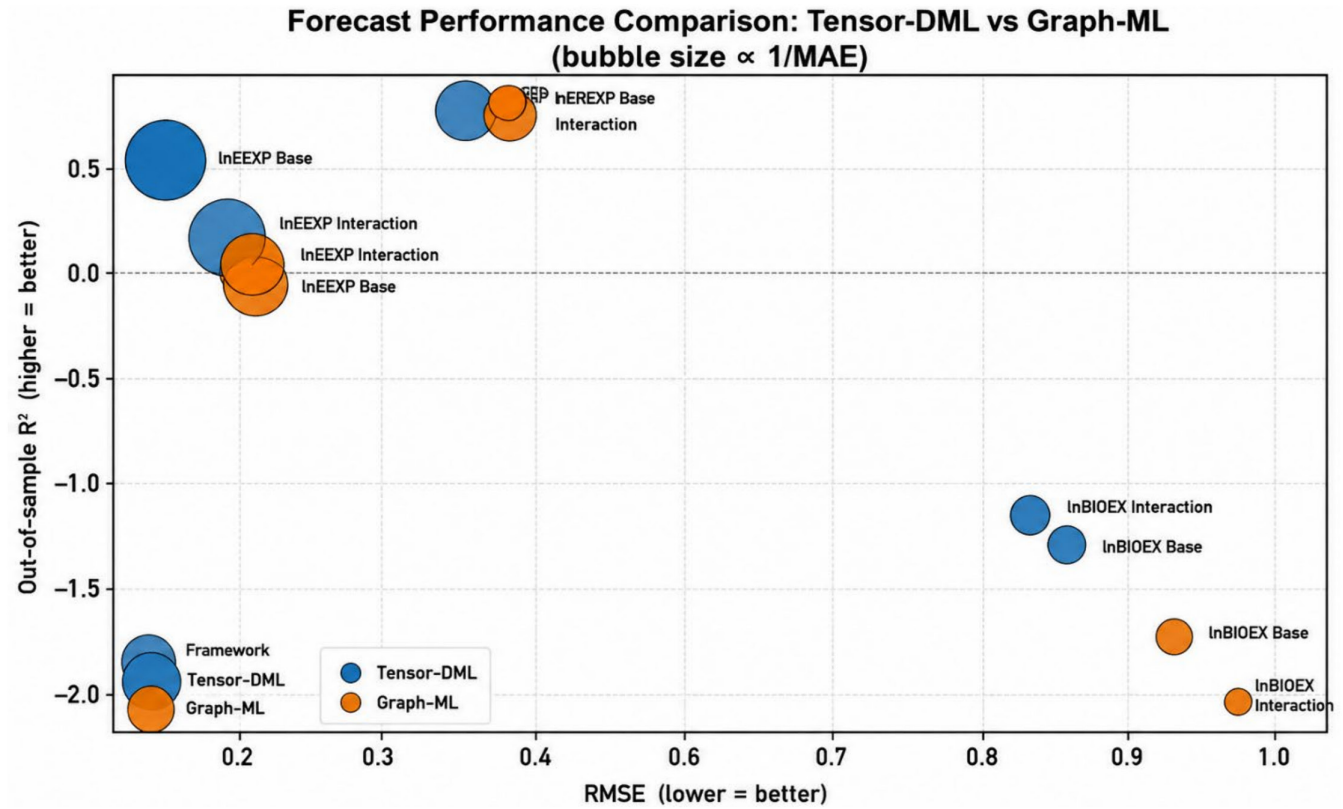


FIGURE 3 | Combined forecast performance map. *Note:* Each marker is one model–specification combination, positioned by RMSE (horizontal) and out-of-sample R^2 (vertical); marker size is proportional to 1/MAE, so larger and upper left markers denote superior performance. Tensor-DML combinations cluster in the high-R^2, low-RMSE region, confirming its overall dominance.

10990836, 0, Downloaded from https://onlinelibrary.wiley.com/doi/10.1002/bse.71764 by NICE, National Institute for Health and Care Excellence, Wiley Online Library on [19/11/2026]. See the Terms and Conditions (https://onlinelibrary.wiley.com/terms-and-conditions) on Wiley Online Library for rules of use; OA articles are governed by the applicable Creative Commons License

TABLE 13 | D-H causality.

Variables	*lnER*	*lnSE*	*lnFinTech*	*lnIQ*	*lnGDP*	*lnEExp*	*lnBio*
lnER	—	↔***	→***	←**	↔***	—	—
lnSE	↔***	—	→***	←***	↔***	→***	↔**
lnFinTech	←***	←***	—	↔***	↔***	—	↔***
lnIQ	→**	→***	↔***	—	→***	→***	—
lnGDP	↔***	↔***	↔***	←***	—	↔***	↔*
lnEExp	—	←***	—	←***	↔***	—	↔***
lnBio	—	↔**	↔***	—	↔*	↔***	—

Note: → and ← represent unidirectional causality with direction "to" and "from." ↔ is bidirectional (feedback) causality, and — indicates no significant causal relationship at the 10% level.
***$p < 0.01$.
**$p < 0.05$.
*$p < 0.10$.

modeled. The single case of no advantage is the lnEEXP interaction model ($p = 0.242$), where the added complexity erodes any predictive edge. Overall, Tensor-DML statistically dominates Graph-ML in most cases, with the lnER difference marginal—evidence that the predictive structure in these data is nonlinear rather than primarily relational, and that the predictive hierarchy (revenue strongly predictable, expenditure moderately so, biodiversity not predictable) independently reflects the structural hierarchy obtained from the econometric estimates.

4.3.1 | Causality Relationships

Table 13 reports the Dumitrescu and Hurlin (2012) findings. The results indicate bidirectional causality between SE and environmental revenue, indicating that each variable predicts the other over time rather than establishing a structural causal effect in either direction. This interdependence between the variables is consistent with the joint-determination concern noted in the estimation strategy. A unidirectional causality from SE to environmental expenditure is consistent with the earlier finding that informality is associated with lower public environmental budget allocation, and a unidirectional relationship from FinTech to both environmental revenue and expenditure is consistent with the interpretation of financial digitalization as a facilitator of fiscal capacity.

The results report a bidirectional causality between SE and biodiversity finance. This indicates that, on the one hand, SE reduces biodiversity finance through fiscal erosion and enforcement capacity channels. On the other hand, biodiversity protection measures may be associated with informality through the enforcement displacement effect, as over-strict conservation regulations, mining limitations, and protected-area restrictions can push small-scale, rural, and traditional businesses to operate outside the formal economy. Modeling biodiversity expenditure as part of a temporal feedback system with SE, rather than as a one-directional outcome, is a useful empirical contribution, though it describes predictive interdependence rather than a structural causal mechanism.

5 | Conclusion

This study examined how SE affects environmental fiscal capacity (environmental tax revenue and environmental and biodiversity expenditures) and whether FinTech moderates these relationships across OECD countries, from 2004 to 2022. The literature has extensively examined the environmental impacts of SE and its effect on the fiscal instruments that finance environmental policy under the Paris Agreement, and the Kunming–Montreal Framework has remained largely unexamined. Using the CCEMG estimator, with Driscoll–Kraay fixed effects and one-step GMM as robustness checks and Dumitrescu–Hurlin causality tests, three findings are robust across all estimators.

The findings reveal that SE significantly decreases environmental tax revenue (most strongly) and public environmental and biodiversity expenditure, consistent with SE reducing environmental fiscal capacity. FinTech development can mitigate the adverse impact of SE on public environmental fiscal capacity.

Complementing the econometric evidence, the machine-learning forecasting exercise reinforced these conclusions from a predictive standpoint. Environmental tax revenue proved strongly forecastable from informality, income, and FinTech, and public environmental expenditure moderately so, whereas the biodiversity-finance models performed poorly, with negative out-of-sample R-squared values indicating that they did not predict better than a naive historical mean. This weak predictive performance should be read as evidence that informality, income, and FinTech do not forecast biodiversity finance well within this sample and measurement framework, consistent with its discretionary and heterogeneously measured character, rather than as proof that biodiversity allocation is inherently unpredictable. The Tensor-DML framework consistently dominated the Graph-ML alternative, indicating that the predictive structure in these data is nonlinear rather than primarily relational.

10990836, 0, Downloaded from https://onlinelibrary.wiley.com/doi/10.1002/bse.71764 by NICE, National Institute for Health and Care Excellence, Wiley Online Library on [19/11/2026]. See the Terms and Conditions (https://onlinelibrary.wiley.com/terms-and-conditions) on Wiley Online Library for rules of use; OA articles are governed by the applicable Creative Commons License

5.1 | Policy Implications

This study carries several policy implications based on empirical analysis. First, the strong negative revenue–SE association implies that environmental tax reform should be embedded within a broader formalization strategy, since higher rates yield diminishing returns on a narrow-documented base; simplified registration for micro-enterprises, integrated tax and social-security registration, and transparent revenue circulation could play a vital role.

Second, and most concretely, the positive revenue–digitalization relationship supports specific digital–fiscal instruments rather than broad governance reform. Mandatory electronic invoicing integrated with tax-authority systems, real-time digital VAT and sales reporting, subsidized point-of-sale infrastructure with digital-acceptance thresholds, and blockchain-based or distributed-ledger reporting providing tamper-evident audit trails for environmental-tax-relevant flows such as fuel distribution, emissions permits, and resource-extraction volumes. These strategies help transformation from informality toward the formal sector of the economy.

Third, because SE reduces biodiversity expenditure, digitalization pushes it further down, and it is the least structurally predictable outcome, biodiversity finance cannot be secured through the same base-broadening levers and requires dedicated protection: ring-fenced or earmarked funding, biodiversity-risk screening in digital-credit underwriting, and complementary private instruments such as biodiversity bonds and debt-for-nature swaps. Its bidirectional relationship with SE indicates that enforcement-heavy conservation without livelihood alternatives can displace users into informality, so biodiversity finance design should integrate with rural-livelihood policy. Finally, because these channels cross ministerial boundaries, coordinated reform across fiscal, digital, and institutional domains, supported by Kunming–Montreal–aligned biodiversity-expenditure tagging, is necessary.

5.2 | Limitations of the Study

The study generated the FinTech index from three components, which partially cover FinTech in a broader sense, and this limitation can be addressed in future studies.

Author Contributions

Sami Ur Rahman: conceptualization, methodology, writing – review and editing, writing – original draft, investigation, formal analysis, software. **Muhammad Ibrahim Khan:** conceptualization, writing – review and editing, supervision. **Javed Hussain:** supervision, writing – review and editing. **Imran Ali Khan:** formal analysis, software.

Disclosure

The authors acknowledged that this study is the original work of the authors and has not been published before.

Conflicts of Interest

The authors declare no conflicts of interest.

References

Alkaseasbeh, M., T. Alqurran, and M. M. A. Orabi. 2023. "Role of Fintech in Uncovering Parallel Economy Initiatives Among Household Business Intrapreneurs." *Journal of System and Management Sciences* 13, no. 5: 413–429.

Arellano, M., and O. Bover. 1995. "Another Look at the Instrumental Variable Estimation of Error-Components Models." *Journal of Econometrics* 68, no. 1: 29–51.

Aron, J. 2018. "Mobile Money and the Economy: A Review of the Evidence." *World Bank Research Observer* 33, no. 2: 135–188.

Athey, S., and G. W. Imbens. 2019. "Machine Learning Methods That Economists Should Know About." *Annual Review of Economics* 11, no. 1: 685–725.

Awosusi, A. A., T. S. Adebayo, M. Altuntaş, E. B. Agyekum, H. M. Zawbaa, and S. Kamel. 2022. "The Dynamic Impact of Biomass and Natural Resources on Ecological Footprint in BRICS Economies: A Quantile Regression Evidence." *Energy Reports* 8: 1979–1994.

Babar, Z. N., and W. Wu. 2025. "Advancing Green Finance Through FinTech Innovations: A Conceptual Insight Into Opportunities and Challenges." *Journal of Excellence in Management Sciences* 4, no. 1: 18–33.

Bahar, M. 2022. "Islamic Economic Development in Indonesia Through the Implementation of Sharia Fintech." *Journal Ilmiah Manajemen, Ekonomi, & Akuntansi (MEA)* 6, no. 3: 761–773.

Baksi, S., and P. Bose. 2016. "Informal Sector, Regulatory Compliance, and Leakage." *Journal of Development Economics* 121: 166–176.

Baloch, M. A., I. Ozturk, F. V. Bekun, and D. Khan. 2022. "Modeling the Dynamic Linkage Between Financial Development, Energy Innovation, and Environmental Quality: Does Globalization Matter?" *Business Strategy and the Environment* 30, no. 1: 176–184.

Besley, T., E. Ilzetzki, and T. Persson. 2013. "Weak States and Steady States: The Dynamics of Fiscal Capacity." *American Economic Journal: Macroeconomics* 5, no. 4: 205–235.

Besley, T., and T. Persson. 2013. "Taxation and Development." In *Handbook of Public Economics*, vol. 5, 51–110. Elsevier.

Biswas, A. K., M. R. Farzanegan, and M. Thum. 2012. "Pollution, Shadow Economy and Corruption: Theory and Evidence." *Ecological Economics* 75: 114–125.

Bitassa, B., M. Pilo, and E. T. Soro. 2025. "From Formalization to Substitutability: Exploring the Role of Political Stability in the Impact of the Shadow Economy on Green Growth in Developing Countries." *Journal of Environmental Management* 394: 127581.

Blackburn, K., N. Bose, and S. Capasso. 2012. "Tax Evasion, the Underground Economy and Financial Development." *Journal of Economic Behavior & Organization* 83, no. 2: 243–253.

Blundell, R., and S. Bond. 1998. "Initial Conditions and Moment Restrictions in Dynamic Panel Data Models." *Journal of Econometrics* 87, no. 1: 115–143.

Brashares, J. S., B. Abrahms, K. J. Fiorella, et al. 2014. "Wildlife Decline and Social Conflict." *Science* 345, no. 6195: 376–378.

Cheng, X., D. Yao, Y. Qian, B. Wang, and D. Zhang. 2023. "How Does Fintech Influence Carbon Emissions: Evidence From China's Prefecture-Level Cities." *International Review of Financial Analysis* 87: 102655.

Chernozhukov, V., D. Chetverikov, M. Demirer, et al. 2018. "Double/Debiased Machine Learning for Treatment and Structural Parameters." *Econometrics Journal* 21, no. 1: C1–C68.

Chien, F., Y. Zhang, and M. Sadiq. 2025. "Fintech Innovation in Green Finance: A Disruptive Force or a Complementary Tool?" *International Review of Economics and Finance* 104: 104658.

10990836, 0, Downloaded from https://onlinelibrary.wiley.com/doi/10.1002/bse.71764 by NICE, National Institute for Health and Care Excellence, Wiley Online Library on [19/11/2026]. See the Terms and Conditions (https://onlinelibrary.wiley.com/terms-and-conditions) on Wiley Online Library for rules of use; OA articles are governed by the applicable Creative Commons License

Copeland, B. R., and M. S. Taylor. 1994. "North-South Trade and the Environment." *Quarterly Journal of Economics* 109, no. 3: 755–787.

Dada, J. T., F. M. Ajide, and M. Arnaut. 2023. "Income Inequality, Shadow Economy and Environmental Degradation in Africa: Quantile Regression via Moment's Approach." *International Journal of Development Issues* 22, no. 2: 214–240.

Dada, J. T., F. M. Ajide, and A. Sharimakin. 2021. "Shadow Economy, Institutions and Environmental Pollution: Insights From Africa." *World Journal of Science, Technology and Sustainable Development* 18, no. 2: 153–171.

Deutz, A., G. M. Heal, R. Niu, et al. 2020. "Financing Nature: Closing the Global Biodiversity Financing Gap. "The Paulson Institute. The Nature Conservancy. The Cornell Atkinson Center for Sustainability.

Diamond, D. W. 1984. "Financial Intermediation and Delegated Monitoring." *Review of Economic Studies* 51, no. 3: 393–414.

Dreher, A., C. Kotsogiannis, and S. McCorriston. 2009. "How Do Institutions Affect Corruption and the Shadow Economy?" *International Tax and Public Finance* 16, no. 6: 773–796.

Dreher, A., and F. Schneider. 2010. "Corruption and the Shadow Economy: An Empirical Analysis." *Public Choice* 144, no. 1: 215–238.

Dumitrescu, E.-I., and C. Hurlin. 2012. "Testing for Granger Non-Causality in Heterogeneous Panels." *Economic Modelling* 29, no. 4: 1450–1460.

Eberhardt, M., and F. Teal. 2011. "Econometrics for Grumblers: A New Look at the Literature on Cross-Country Growth Empirics." *Journal of Economic Surveys* 25, no. 1: 109–155.

Elgin, C., M. A. Kose, F. Ohnsorge, and S. Yu. 2021. "Understanding Informality." CEPR Discussion Paper No. 16497.

Elgin, C., and O. Oztunali. 2014. "Pollution and Informal Economy." *Economic Systems* 38, no. 3: 333–349.

Feng, Y., Y. Cao, and J. Ni. 2023. "Does Fintech Affect Shadow Banking of Non-Financial Firms? Evidence From the Entrusted Loans." *International Review of Financial Analysis* 94: 103268.

GBF, M. 2022. "Kunming-Montreal Global Biodiversity Framework." In *The Fifteenth Meeting of the Conference of the Parties to the Convention on Biological Diversity (Part Two), Decision 15/4*.

Grossman, G. M., and A. B. Krueger. 1995. "Economic Growth and the Environment." *Quarterly Journal of Economics* 110, no. 2: 353–377.

Guan, X., A. Hassan, and A. A. Nassani. 2025. "Investigating the Role of Environmental Taxes, Green Finance, Natural Resources, Human Capital, and Economic Growth on Environmental Pollution Using Panel Quantile Regression." *Sustainability* 17, no. 3: 1094.

Halkos, G. E., and E. A. Paizanos. 2013. "The Effect of Government Expenditure on the Environment: An Empirical Investigation." *Ecological Economics* 91: 48–56.

Hanley, N., and E. B. Barbier. 2009. *Pricing Nature: Cost-Benefit Analysis and Environmental Policy*. Edward Elgar Publishing.

Horn, M., A. Dabbous, A. Oehler, and F. Göbel. 2026. "Determinants and Effects of Green Bond Issuance: Environmental Awareness, Ecological Budget, Biodiversity, Oil and Lithium." *Ecological Economics* 239: 108753.

Hussain, M., and E. Dogan. 2021. "The Role of Institutional Quality and Environment-Related Technologies in Environmental Degradation for BRICS." *Journal of Cleaner Production* 304: 127059.

Immordino, G., and F. F. Russo. 2018. "Cashless Payments and Tax Evasion." *European Journal of Political Economy* 55: 36–43.

Khan, I., and M. S. Shahid. 2025. "The Nexus Between Fintech and Green Finance in Advancing Sustainable Performance Across Countries." *Discover Sustainability* 7, no. 1: 49.

Khera, P., S. Ng, S. Ogawa, and R. Sahay. 2022. "Measuring Digital Financial Inclusion in Emerging Market and Developing Economies: A New Index." *Asian Economic Policy Review* 17, no. 2: 213–230.

Kipf, T. N., and M. Welling. 2017. "Semi-Supervised Classification With Graph Convolutional Networks." International Conference on Learning Representations (ICLR).

Kshetri, N., and E. Loukoianova. 2019. "Blockchain Adoption in Supply Chain Networks in Asia." *IT Professional* 21, no. 1: 11–15.

Levine, R. 1997. "Financial Development and Economic Growth: Views and Agenda." *Journal of Economic Literature* 35, no. 2: 688–726.

López, R., G. I. Galinato, and A. Islam. 2011. "Fiscal Spending and the Environment: Theory and Empirics." *Journal of Environmental Economics and Management* 62, no. 2: 180–198.

Magazzino, C., M. Mele, and N. Schneider. 2021. "A Machine Learning Approach on the Relationship Among Solar and Wind Energy Production, Coal Consumption, GDP, and CO_2 Emissions." *Renewable Energy* 167: 99–115.

Markandya, A., M. González-Eguino, and M. Escapa. 2013. "From Shadow to Green: Linking Environmental Fiscal Reforms and the Informal Economy." *Energy Economics* 40: S108–S118.

Medina, L., and F. Schneider. 2019. "Shedding Light on the Shadow Economy: A Global Database and the Interaction With the Official One." CESifo Working Paper.

Medina, L., and M. F. Schneider. 2018. *Shadow Economies Around the World: What Did We Learn Over the Last 20 Years? International Monetary Fund*. International Monetary Fund.

Mullainathan, S., and J. Spiess. 2017. "Machine Learning: An Applied Econometric Approach." *Journal of Economic Perspectives* 31, no. 2: 87–106.

Nellemann, C., R. Henriksen, A. Kreilhuber, et al. 2016. *The Rise of Environmental Crime: A Growing Threat to Natural Resources, Peace, Development and Security*. UNEP-INTERPOL.

Nguyen, C. P., N. Doan, H. Doan, C. T. Nguyen, and B. Q. Nguyen. 2026. "Environmental Taxes and the Economy: New Evidence of the Shadow Economy." *Annals of Public and Cooperative Economics* 97: 731–756.

OECD. 2021. *Financial Markets and Climate Transition: Opportunities, Challenges and Policy Implications*. OECD Publishing.

Ozili, P. K. 2018. "Impact of Digital Finance on Financial Inclusion and Stability." *Borsa Istanbul Review* 18, no. 4: 329–340.

Organisation for Economic Co-operation and Development. 2020. *A Comprehensive Overview of Global Biodiversity Finance*. OECD Publishing. https://doi.org/10.1787/5e9ec2fc-en.

Organisation for Economic Co-operation and Development. 2023. *Methodological Guidelines for Compiling Environmentally Related Tax Revenue Accounts*. OECD Publishing. https://doi.org/10.1787/d752d120-en.

Pesaran, M. H. 2004. "General Diagnostic Tests for Cross Section Dependence in Panels." CESifo Working Paper No. 1229.

Pesaran, M. H. 2006. "Estimation and Inference in Large Heterogeneous Panels With a Multifactor Error Structure." *Econometrica* 74, no. 4: 967–1012.

Pesaran, M. H. 2007. "A Simple Panel Unit Root Test in the Presence of Cross-Section Dependence." *Journal of Applied Econometrics* 22, no. 2: 265–312.

Pesaran, M. H., and R. Smith. 1995. "Estimating Long-Run Relationships From Dynamic Heterogeneous Panels." *Journal of Econometrics* 68, no. 1: 79–113.

Pesaran, M. H., and T. Yamagata. 2008. "Testing Slope Homogeneity in Large Panels." *Journal of Econometrics* 142, no. 1: 50–93.

10990836, 0, Downloaded from https://onlinelibrary.wiley.com/doi/10.1002/bse.71764 by NICE, National Institute for Health and Care Excellence, Wiley Online Library on [19/11/2026]. See the Terms and Conditions (https://onlinelibrary.wiley.com/terms-and-conditions) on Wiley Online Library for rules of use; OA articles are governed by the applicable Creative Commons License

Qin, L., G. Aziz, M. W. Hussan, A. Qadeer, and S. Sarwar. 2024. "Empirical Evidence of Fintech and Green Environment: Using Green Finance as a Mediating Variable." *International Review of Economics and Finance* 89, no. Part A: 33–49.

Rahman, M. M. 2023. "Impact of Taxes on the 2030 Agenda for Sustainable Development: Evidence From OECD Countries." *Regional Sustainability* 4, no. 3: 235–248.

Rahman, S. U., F. Faisal, A. Ali, H. G. H. Sulimany, and A. H. Bazhair. 2023. "Do Financial Technology and Financial Development Lessen Shadow Economy? Evidence From BRICST Economies Using Heterogenous Bootstrap Panel Causality." *Quarterly Review of Economics and Finance* 90: 201–210.

Rahman, S. U., I. A. Khan, F. Sami, J. Hussain, and M. I. Khan. 2025. "From Shadow to Sustainability: How Informality, Environmental Taxes, and Green Innovation Reshape Carbon and Biodiversity Futures in the G7 Countries." *Journal of Environmental Management* 393: 127153.

Rahman, S. U., M. I. Khan, J. Hussain, and I. A. Khan. 2026. "From Informality to Green Development: How the Shadow Economy Affects Green Finance, Green Innovation, and Green Trade." *Business Strategy and the Environment*.

Roodman, D. 2009. "How to Do xtabond2: An Introduction to Difference and System GMM in Stata." *Stata Journal: Promoting Communications on Statistics and Stata* 9, no. 1: 86–136.

Sahay, R., U. E. von Allmen, A. Lahreche, et al. 2020. *The Promise of Fintech: Financial Inclusion in the Post COVID-19 Era*. International Monetary Fund.

Schneider, F. 2022. "New COVID-Related Results for Estimating the Shadow Economy in the Global Economy in 2021 and 2022." *International Economics and Economic Policy* 19, no. 2: 299–313.

Schneider, F. G. 2002. "The Size and Development of the Shadow Economies of 22 Transition and 21 OECD Countries (No. 514)." IZA Discussion Papers.

Storm, H., K. Baylis, and T. Heckelei. 2020. "Machine Learning in Agricultural and Applied Economics." *European Review of Agricultural Economics* 47, no. 3: 849–892.

Sundström, A. 2016. "Understanding Illegality and Corruption in Forest Governance." *Journal of Environmental Management* 181: 779–790.

Suri, T., and W. Jack. 2016. "The Long-Run Poverty and Gender Impacts of Mobile Money." *Science* 354, no. 6317: 1288–1292.

Syed, A. A., F. Ahmed, M. A. Kamal, and J. E. Trinidad Segovia. 2021. "Assessing the Role of Digital Finance on Shadow Economy and Financial Instability: An Empirical Analysis of Selected South Asian Countries." *Mathematics* 9, no. 23: 3018.

United Nations. 2015. "Paris Agreement. https://unfccc.int/sites/default/files/english_paris_agreement.pdf.

United Nations Development Programme. 2024. "BIOFIN Workbook 2024: Finance for Nature." https://www.biofin.org/knowledge-product/biofin-2024-workbook/.

Wang, T., M. Umar, M. Li, and S. Shan. 2023. "Green Finance and Clean Taxes Are the Ways to Curb Carbon Emissions: An OECD Experience." *Energy Economics* 124: 106842.

Wang, Y., V. M. Antohi, C. Fortea, et al. 2024. "Shadow Economy and Environmental Sustainability in Global Developing Countries: Do Governance Indicators Play a Role?" *Sustainability* 16, no. 22: 9852.

Wei, Z., A. Iqbal, S. Jahangir, M. S. E. Ali, and M. Hussain. 2025. "Financing the Green Transition: How Green Finance, Green Innovation, Green Growth, and Environmental Taxes Can Drive Carbon Neutrality." *Environment, Development and Sustainability*: 1–33.

Westerlund, J. 2007. "Testing for Error Correction in Panel Data." *Oxford Bulletin of Economics and Statistics* 69, no. 6: 709–748.

Zhang, Q., J. Que, and X. Qin. 2023. "Regional Financial Technology and Shadow Banking Activities of Non-Financial Firms: Evidence From China." *Journal of Asian Economics* 86: 101606.

Appendix A

OECD countries		
Australia, Austria	Finland	Netherlands, Norway
Belgium	Germany, Greece	Latvia, Lithuania, Luxembourg
Czech Republic	Hungary	Poland
Denmark	Ireland, Italy	Slovak Republic, Slovenia, Spain
Estonia	Japan	Sweden, Switzerland

10990836, 0, Downloaded from https://onlinelibrary.wiley.com/doi/10.1002/bse.71764 by NICE, National Institute for Health and Care Excellence, Wiley Online Library on [19/11/2026]. See the Terms and Conditions (https://onlinelibrary.wiley.com/terms-and-conditions) on Wiley Online Library for rules of use; OA articles are governed by the applicable Creative Commons License