Climate Risk and Bank Efficiency: The Moderating Role of Financial Derivatives and Carbon Disclosure

Kieu-Thi Phan[1], Sheng-Hung Chen[2], Hsin-Yi Huang[3,*]

[1] PhD, Statistics Office of Vinh Long (under the management of the General Statistics Office of Viet Nam); Department of International Business, National Kaohsiung University of Science and Technology, Kaohsiung, Taiwan. Email: i110159113@nkust.edu.tw

[2] Professor, Department of International Business, National Kaohsiung University of Science and Technology, Kaohsiung, Taiwan. Email: shchenib@nkust.edu.tw

[3] Associate Professor, Department of Finance, National Taichung University of Science and Technology, Taichung, Taiwan. Email: hsinyi@nutc.edu.tw

*Corresponding author

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Abstract

This study examines how climate risk influences bank efficiency, highlighting the moderating roles of financial derivatives and carbon disclosure practices. Employing a panel dataset of 1,175 banks across 69 countries from 2001 to 2021, this study applies advanced techniques—Data Envelopment Analysis (DEA) and the Malmquist-Luenberger productivity index—to estimate technical efficiency (CRSTE) and pure technical efficiency (VRSTE). Then, truncated regression is employed to evaluate how climate risk affects bank efficiency measures. The findings indicate that climate risk significantly impairs bank efficiency. However, the study also uncovers a mitigating effect—banks that utilize financial derivatives, whether for hedging or trading purposes, are better positioned to buffer against this efficiency loss. Moreover, proactive engagement in carbon disclosure, particularly through the Carbon Disclosure Project (CDP) reporting, further alleviates the adverse effects of climate risk. Notably, banks with high ESG performance and transparent reporting practices achieve higher efficiency and demonstrate greater resilience to climate-related shocks. These results offer new theoretical and empirical insights into how banks can integrate climate risk management tools into efficiency strategies. Our findings provide practical insights for financial regulators, bank leaders, and policymakers focused on enhancing resilience against rising climate risks.

Keywords: Climate Risk, Bank Efficiency, Financial Derivatives, CDP Disclosure, ESG Performance, DEA-Malmquist, Truncated Regression

Key Findings:

- Climate risk significantly reduces bank efficiency;
- Financial derivatives and carbon disclosure initiatives enhance efficiency;
- Financial derivatives and carbon disclosure effectively mitigate the adverse impact of climate risk;
- Better ESG performance supports bank efficiency and resilience in the face of climate risk.

1. Introduction

Climate risk has rapidly become a critical concern for financial institutions, particularly banks, which form the cornerstone of financial intermediation and systemic stability. The increasing frequency and severity of climate-induced phenomena—ranging from extreme weather events to abrupt regulatory transitions—pose both physical and transition risks to financial assets and lending portfolios. As financial intermediaries, banks are particularly vulnerable due to their long-duration assets and complex exposures. In recognition of these risks, regulators and stakeholders require that banks consider climate considerations in their core operations, such as credit allocation, risk assessment, and climate-related disclosure practices.

In response, banks have begun to adopt climate-related scenario analysis, integrate ESG practices, and align disclosures with global frameworks such as the TCFD and CDP. In parallel, derivatives—ranging from weather derivatives to carbon futures—have emerged as valuable instruments for hedging the volatility and uncertainty tied to climate-related risks, including commodity price fluctuations and environmental liabilities.

Although the literature on climate finance has expanded rapidly, two persistent gaps remain. First, empirical studies often examine climate risk and financial performance in isolation (Battiston et al., 2017; Berger & Humphrey, 1997; Engle et al., 2020; Ilhan et al., 2021; Mamatzakis et al., 2008), without integrating these variables into operational efficiency models. Second, while financial derivatives as hedging instruments are well-established in general risk management (Stulz, 2022), their role in climate-specific contexts remains under-theorized and under-explored empirically. Likewise, although disclosure frameworks such as the CDP and TCFD have gained regulatory traction, there is limited understanding of how such disclosures interact with climate risk and operational efficiency.

This study responds to these gaps by integrating theories from financial intermediation, sustainable finance, and stakeholder management. This study proposes and tests a framework in which climate risk (CRISK) impairs bank efficiency while derivative usage and high-quality climate disclosures act as moderating mechanisms. Our contribution is threefold. First, this study estimates technical efficiency using the DEA-Malmquist approach, then incorporates CRISK as a core explanatory variable in a truncated model. Second, this study operationalizes and tests the moderating role of financial derivatives and carbon disclosure in controlling climate-related risks. Third, we assess how ESG performance jointly influences banks' technical efficiency.

This study draws upon an international panel dataset of banks from 2001 to 2021, combining traditional balance sheet variables with hand-collected information on derivative usage from annual reports and U.S. Call Reports. This dataset captures the gross notional value of derivatives, distinguishing between hedging and trading functions—a methodological improvement over binary classifications in existing studies. By incorporating CDP disclosure and ESG performance, this study offers a multidimensional analysis of how financial and informational strategies shape climate-adjusted efficiency. In methodological alignment with recent advancements (Akdeniz et al., 2023; Pasiouras, 2008), the study employs non-interest expenses as inputs and non-interest income as outputs to evaluate performance. This analytical approach not only deepens our understanding of climate-adjusted bank efficiency but also provides a template for future research on financial innovation in sustainable finance.

Beyond academic contribution, our findings have direct implications for both regulators and bank managers. As climate stress testing becomes institutionalized, our results underscore the need to integrate derivative strategies and disclosure quality into regulatory assessments of bank resilience. For managers, the results suggest that proactive climate hedging and transparent ESG-aligned disclosures can enhance operational efficiency and strategic competitiveness in an increasingly sustainability-driven market environment. Within this framework, the study explores the following questions: To what extent does climate risk (CRISK) impact bank efficiency? How do financial derivatives influence the relationship between climate risk and efficiency? Do carbon disclosures alleviate the adverse effects of climate risk on efficiency? Additionally, how do ESG performance and the quality of carbon disclosures interact to affect bank efficiency?

2. Literature Review and Hypothesis Development

2.1 Theoretical foundations

The analysis of climate risk and bank efficiency requires a multidimensional theoretical framework that integrates insights from financial intermediation theory, risk management, climate finance, and technical efficiency. Each perspective provides unique insights into bank behavior and performance, but they all become particularly important during environmental disruptions that challenge banks' adaptability and resilience.

Financial intermediation theory conceptualizes banks as entities that transform financial inputs—such as labor, deposits, and capital—into outputs that include loans, investments, and payment services. Sealey and Lindley (1977) have formalized this approach within a production framework, which has since become foundational to bank efficiency research. Berger and Humphrey (1997) have extended this work, highlighting how institutional and regulatory environments influence intermediation quality and efficiency across countries. More recently, studies such as Mamatzakis et al. (2008) and Koutsomanoli-Filippaki et al. (2009) employ frontier-based methods to examine how structural reforms, market discipline, and competition affect bank efficiency in European and transitional banking systems. In the context of climate risk, financial intermediation theory offers a lens to assess how banks reallocate resources in response to climate-related disruptions. As climate risk affects borrowers' creditworthiness and asset values, efficient intermediation becomes essential for reallocating capital toward sustainable sectors while maintaining liquidity and profitability. This perspective provides the theoretical grounding for examining how climate risk challenges the efficiency of capital deployment within the banking sector.

Modern risk management theories explain how financial institutions mitigate exposure to various forms of uncertainty through portfolio diversification, capital buffers, and hedging strategies. Peristiani (1997) has linked bank mergers and diversification strategies to improvements in X-efficiency, while Li and Marinč (2014) and Mayordomo et al. (2014) have explored how derivatives can reduce bank-specific risks, albeit with potentially systemic consequences. Titova et al. (2020) have provided empirical evidence from European banks, showing that well-governed derivative use enhances financial stability and performance. Zakaria (2017) demonstrates that risk management practices are integral to operational efficiency by using DEA models. These insights are particularly relevant to climate risk, which introduces complex, forward-looking, and often non-linear exposures. Derivatives may serve as hedging tools for banks seeking to manage interest rates, energy prices, or weather-related risks. However, their efficiency-enhancing role depends on whether they are deployed strategically to reduce exposure or speculatively to increase returns. Thus, risk management theory informs the proposition that appropriate derivative use can moderate the adverse impact of climate risk on bank efficiency.

The growing importance of climate-related risks in finance has generated a new body of theory emphasizing the need for banks to align operational practices with environmental considerations. Climate finance theory incorporates both regulatory frameworks—such as Basel III and the Task Force on Climate-related Financial Disclosures (TCFD)—and market-driven ESG integration. Empirical studies show that banks responding to climate risk through disclosure, capital reallocation, and sustainable finance tend to be more resilient. For instance, Caby et al. (2022) and Adu and Roni (2024) have found that ESG-oriented banks exhibit superior profitability and risk-adjusted performance. Lee et al. (2022) and Lang et al. (2023) have documented how climate risk exposure alters liquidity creation and lending decisions across jurisdictions. Acharya et al. (2023) demonstrated that climate stress testing can reveal systemic vulnerabilities under transition scenarios. These insights suggest that climate disclosures and governance mechanisms may mitigate the operational inefficiencies induced by climate shocks. As a result, climate finance theory underpins the argument that proactive environmental risk management—especially through transparency and disclosure—enhances the technical efficiency of banking operations.

Technical efficiency refers to the ability of a decision-making unit (DMU), such as a bank, to produce the maximum output from a given input set or, conversely, to minimize inputs for a specified output level. Farrell (1957) introduced the distinction between technical and allocative efficiency, laying the groundwork for later measurement tools. Aigner et al. (1977) and Meeusen and van Den Broeck (1977) developed Stochastic Frontier Analysis (SFA), which incorporates statistical noise into inefficiency estimation. Charnes et al. (1978) introduced Data Envelopment Analysis (DEA), a non-parametric approach later extended to accommodate scale heterogeneity by Banker et al. (1984).

Subsequent models addressed the complexity of banking operations. Seiford and Zhu (1999) have incorporated profitability and marketability into DEA models, while Fukuyama and Weber (2010) have introduced slacks-based approaches for evaluating systems with undesirable outputs—relevant for institutions managing both financial performance and environmental externalities. More recently, Zhu (2022) has advanced network DEA models that capture interconnected production processes across on- and off-balance-sheet banking activities, providing a dynamic and granular view of institutional efficiency. Incorporating climate variables into these frameworks enables the examination of how external shocks influence frontier positioning and managerial performance. Accordingly, technical efficiency theory supports the empirical approach of this study, which uses frontier analysis to evaluate how climate risk, hedging, and disclosure jointly affect bank efficiency.

The integration of financial intermediation, risk management, climate finance, and technical efficiency theories offers a comprehensive framework to analyze how banks respond to environmental risk. While financial intermediation theory explains the reallocation of resources in response to climate-related shocks, risk management theory highlights the strategic role of financial instruments. Climate finance theory underscores the institutional and regulatory dimensions of environmental integration, and technical efficiency theory provides the methodological foundation for performance measurement. In short, these theories argue that a bank’s efficiency regarding climate risk depends not only on its environmental exposure but also on its ability to adapt through risk mitigation and transparency mechanisms.

2.2 Technical efficiency measurement using Data Envelopment Analysis (DEA)

The DEA approach has emerged as a widely used non-parametric technique for assessing the technical efficiency of banks, particularly in cross-country studies where assumptions about functional form and error distribution may be restrictive (Berger & Humphrey, 1997; Fukuyama & Weber, 2010). DEA models assess the relative efficiency of decision-making units (DMUs) by constructing an empirical production frontier based on observed input-output combinations. In the banking context, inputs typically include labor, capital, and deposits, while outputs may encompass loans, interest income, or non-interest revenue (Drake et al., 2006).

A key advantage of DEA lies in its flexibility. It does not require the specification of a particular functional form and can accommodate multiple inputs and outputs, which is particularly relevant for capturing the complex production processes of banks (Boussemart et al., 2003). Compared to parametric approaches such as Stochastic Frontier Analysis (SFA), DEA is more suitable for exploratory analysis in heterogeneous settings, especially when the focus is relative rather than absolute efficiency. More recent applications have extended DEA models to incorporate environmental and sustainability-related outputs, enabling researchers to evaluate green efficiency (Taleb, 2023; Zhu, 2022). In addition, Pasiouras (2008) and Pasiouras et al. (2009) utilize two-stage DEA models to analyze how regulatory frameworks affect cost and profit efficiency. Anagnostopoulos et al. (2022) compare efficiency between

U.S. and European banks, while Wu et al. (2023) explore interest rate liberalization’s impact on Chinese banks via DEA. Akdeniz et al. (2023) note a shift in DEA innovations towards dynamic, hybrid, and sustainability-oriented models, incorporating ESG indicators and climate risk. Though DEA effectively handles multiple inputs and outputs, its deterministic nature can make it sensitive to outliers and measurement errors. Despite this, it remains vital for evaluating performance and guiding resource allocation in banking.

Despite the extensive application of DEA to banking efficiency studies, there is limited research on how derivative usage or climate-related risks influence technical efficiency. While some studies have examined the impact of market-based instruments on cost or profit efficiency (Fiordelisi et al., 2011), few have directly linked risk mitigation strategies—such as derivative hedging—to DEA-measured efficiency. Similarly, although climate risk has been shown to influence asset quality and capital allocation (Battiston et al., 2017), its implications for production efficiency remain underexplored. This study addresses these gaps by integrating climate risk measures and derivative usage into a DEA framework, allowing for a more nuanced assessment of bank efficiency in the face of environmental uncertainty.

2.3 Climate risk and bank efficiency

Growing empirical evidence highlights the negative effects of climate risk on bank efficiency. Li and Pan (2022) demonstrate that Chinese banks exposed to carbon-intensive industries exhibit declining profitability and operational efficiency, prompting a reevaluation of credit allocation strategies. Similarly, Zhang et al. (2022) show that natural disasters diminish bank efficiency, underscoring the need for climate-integrated planning. Lee et al. (2024) reinforce these findings by showing that banks with high exposure to climate-sensitive sectors suffer sharp declines in profitability, reinforcing calls for robust climate risk assessment frameworks. Complementary studies explore mechanisms mitigating these risks. Adu and Roni (2024) find that strong corporate governance facilitates the implementation of climate initiatives, enhancing both efficiency and profitability. Liu et al. (2024) show that while climate transition risks heighten risk-taking behaviors in banks, digital transformation can mitigate these effects. Cao et al. (2024) further establish that ESG investments are positively associated with efficiency gains, suggesting that sustainability and financial performance are not mutually exclusive.

Systemic implications are also emphasized. Le et al. (2023), using a sample of over 6,000 banks across 109 countries, have found a consistent negative relationship between climate risk and bank stability. Climate risk's impact on collateral quality (Li et al., 2024) and credit demand (Javadi et al., 2023) further erodes operational efficiency as banks face declining asset valuations and cautious lending behavior. Collectively, these studies indicate that climate risks, unless actively managed, undermine the productivity and strategic agility of banks. Earlier literature also provides foundational support. Chiu and Chen (2009) identify a significant influence of environmental risks on operational efficiency in Taiwanese banks, while Caby et al. (2022) argue that strategic integration of climate considerations can enhance profitability. Macro-level perspectives from Roncoroni et al. (2021) and Wang et al. (2025) stress that institutional and policy support for climate resilience is essential for preserving efficiency during transitions. Finally, empirical findings from Sun and Chang (2011) and Awojobi (2011) in emerging markets reiterate the importance of risk governance in safeguarding efficiency against environmental shocks.

Recent studies show that climate risk significantly alters the structure of financial demand, particularly through its effects on credit allocation and liquidity preferences. Nguyen et al. (2023) and Ding et al. (2023) find that firms with high emissions face tighter lending constraints, as banks increasingly incorporate transition risks into loan pricing. This shift constrains credit availability and drives changes in portfolio composition, particularly in carbon-intensive sectors. Javadi and Masum (2021) provide further evidence that climate change increases borrowing costs, particularly for high-risk borrowers, as banks adjust for future regulatory and reputational risks. Similarly, Agoraki et al. (2024) and Cepni et al. (2024) note that climate exposure raises firms' cost of capital and impairs investment efficiency, resulting in lower demand for bank credit. These dynamics necessitate a shift in how banks assess and price financial risk. Banks' internal liquidity strategies are also evolving. Lang et al. (2023) find that banks facing high climate risk increase liquidity buffers, which, while enhancing resilience, can lead to capital misallocation. Lee et al. (2022) show that heightened climate exposure suppresses banks' liquidity creation capacity, reducing their contribution to economic activity. These studies suggest that climate risk constrains both credit supply and financial intermediation efficiency, especially in emerging markets (Saleh & Abu Afifa, 2020). Taken together, the literature indicates that climate-related pressures reshape financial demand through credit rationing, liquidity hoarding, and pricing adjustments—ultimately impacting banks' core intermediation functions.

The growing combination of climate risk into financial stability analyses reflects its potential to generate widespread systemic disruptions. Feng et al. (2024) demonstrate that exposure to climate change increases firm-level bankruptcy risk, which in turn raises the incidence of non-performing loans. Gupta and Kashiramka (2024) further argue that the stabilizing role of bank liquidity creation depends on robust ESG disclosure practices, suggesting a clear linkage between transparency and macroprudential stability. Institutional variation also matters. Mbanyele and Muchenje (2022) show that banks in developed economies adopt more comprehensive climate risk management strategies, while Hossain and Masum (2022) highlight the value of CSR practices in enhancing creditworthiness and stability in emerging markets. These findings underscore the role of governance and disclosure in maintaining stability amid climate-related shocks. From a market perspective, financial innovations such as ESG-linked derivatives and sustainable investment products offer stabilizing tools. Kumar (2023) and Chatjuthamard et al. (2024) report that these instruments help realign investor expectations, while Calvet et al. (2022) highlight the rising global demand for sustainable finance as a stabilizing force in capital markets. However, these benefits hinge on regulatory oversight and market maturity, especially in developing economies.

2.4 Financial derivatives and risk management

The use of derivatives by banks has evolved significantly over the past three decades, with financial institutions increasingly relying on these instruments for hedging, speculative purposes, and balance sheet management (Minton et al., 2009; Vallascas & Hagendorff, 2013). Numerous studies have explored why banks use derivatives and how this practice affects their risk and performance. In developed markets such as the United States and the European Union, derivatives—especially interest rate swaps and foreign exchange contracts—are commonly employed to manage market and credit risk exposures (Khwaja & Mian, 2008). These practices are typically supported by robust regulatory oversight and advanced risk management frameworks. Conversely, in emerging economies, the adoption of derivatives has been more heterogeneous, shaped by regulatory capacity, financial infrastructure, and macroeconomic volatility. While some studies suggest that banks in emerging markets primarily use derivatives for hedging foreign currency exposure (Bartram et al., 2011), others reveal that these instruments may also be employed opportunistically to enhance returns, potentially increasing systemic risk (Chen et al., 2021). The divergence in usage patterns emphasizes the importance of institutional context in influencing the role of derivatives in bank risk management strategies.

Recent literature has begun to explore the connection between derivatives and environmental risk, particularly in climate uncertainty. Instruments such as weather derivatives and catastrophe bonds are increasingly viewed as tools to hedge against physical climate risks (Battiston & Monasterolo, 2019; Scholtens & Sievänen, 2013). However, empirical evidence on the integration of such instruments into mainstream banking operations remains limited, particularly outside high-income jurisdictions. This gap suggests a pressing need to examine whether and how derivatives are deployed by banks to mitigate climate risk and how this usage varies across institutional settings. The current study contributes to this line of inquiry by linking derivative usage with climate risk exposure and bank efficiency across a global sample.

Financial derivatives are now essential for banks' risk management, especially regarding climate risk. Titova et al. (2020) and Li and Marinč (2014) distinguish between derivatives used for hedging—which improve performance and reduce risk—and those used for speculation, which can exacerbate systemic vulnerabilities. Zakaria (2017) and Vuillemey (2019) add that derivatives, when applied strategically, enhance risk governance and optimize return profiles. Recent studies underscore derivatives' evolving role in addressing environmental uncertainties. Do et al. (2024) find that weather derivatives protect borrowers in private debt contracts from repayment volatility induced by climate shocks. Bressan and Romagnoli (2021) and Little et al. (2015) advocate for climate-specific derivatives as tools for enhancing institutional resilience and climate adaptation. Nevertheless, risks remain. Mayordomo et al. (2014) and Instefjord (2005) warn that high reliance on complex derivatives can elevate contagion risk, especially in tightly coupled financial networks. In the African context, Bekale et al. (2024) caution that while derivatives reduce idiosyncratic risk, they may introduce systemic fragility in jurisdictions with weak oversight. Overall, the literature suggests that derivatives can be potent instruments for climate risk management, but their stabilizing potential is contingent on sound governance and regulatory safeguards.

Effective policy and regulation are essential to ensure that financial institutions manage climate risks without undermining system-wide stability. Lannoo and Thomadakis (2020) and Hammoudeh and McAleer (2013) emphasize the strategic role of derivatives in supporting sustainable finance and mitigating macroeconomic volatility. However, as Anderson et al.

(2023) and Sun et al. (2022) point out, derivative use must be embedded within robust regulatory frameworks to ensure that it supports—not undermines—climate-aligned financial transitions. Emerging markets face particular challenges. Bazih and Vanwalleghem (2021) show that the benefits of derivatives in these economies are often diluted by regulatory gaps and institutional weaknesses. These findings suggest a pressing need for capacity-building and policy alignment to foster resilient, climate-conscious financial systems.

2.5 Carbon disclosure and ESG performance

The growing exposure of banks to climate-related risks—both physical and transition—has raised concerns about potential declines in bank efficiency due to increased credit risk, regulatory complexity, and operational disruptions (Battiston et al., 2021; Capasso et al., 2020). However, recent literature identifies corporate sustainability practices—particularly carbon disclosure and ESG performance—as strategic tools that can mitigate these adverse effects and enhance operational resilience. First, carbon disclosure through frameworks enhances transparency about a bank's climate risk exposure, emissions profile, and environmental management strategies. Prior studies suggest that such disclosure reduces information asymmetries between firms and external stakeholders (Depoers et al., 2016; Liesen et al., 2015), thereby lowering perceived risk and the cost of capital (Ben- Amar & McIlkenny, 2015). CDP disclosure also signals a proactive approach to risk management and regulatory preparedness, which can translate into reputational gains and greater stakeholder trust (Bui & De Villiers, 2017). These outcomes foster better access to capital markets, reduce market uncertainty, and improve strategic decision-making—conditions that enhance bank efficiency in the face of environmental uncertainty. Furthermore, carbon disclosure may encourage internal efficiency by promoting systematic tracking of emissions, energy use, and resource allocation, all of which are conducive to streamlined operations (Kölbel et al., 2020).

Second, ESG performance plays a complementary role by embedding environmental and social responsibility into the bank's operational framework. High ESG performers are more likely to adopt energy-efficient practices, develop green financial products, and maintain strong stakeholder relationships (Albuquerque et al., 2019; Fatemi et al., 2018). These attributes not only improve brand equity and client retention but also insulate the institution from climate-related disruptions. Moreover, from a risk management perspective, superior ESG performance is associated with more robust governance structures (Friede et al., 2015), which enhance a bank's ability to anticipate and adapt to climate risks. Empirical evidence indicates that firms with stronger ESG profiles exhibit lower earnings volatility, higher financial resilience, and more efficient capital deployment (Ferriani & Natoli, 2021; Liang & Renneboog, 2017). In this context, ESG engagement can be seen not only as a response to stakeholder pressures but also as a strategic asset that enhances efficiency by fostering long-term value creation. In sum, CDP disclosure and ESG performance provide banks with both informational and capability-based advantages that mitigate the efficiency-reducing effects of climate risk. By improving transparency, reducing risk perceptions, and aligning strategic goals with environmental imperatives, these sustainability practices serve as moderating mechanisms that enable banks to remain operationally efficient even under heightened climate exposure.

3. Hypothesis Development

The increasing prominence of climate risk presents new challenges for banks as financial intermediaries. This study proposes hypotheses based on financial intermediation theory, efficiency theory, risk management literature, and climate finance. It investigates how climate risk affects bank efficiency, the role of derivatives as an adaptive mechanism, and the contribution of climate-related disclosures to strategic resilience. These hypotheses address critical gaps in the empirical literature concerning bank-level operational performance and financial innovation under environmental uncertainty.

Climate risk—whether physical (e.g., extreme weather events) or transition-related (e.g., policy, regulatory, and market changes)—can negatively influence banks' operational performance by increasing loan default risk, elevating compliance costs, and destabilizing asset valuations (Battiston et al., 2017; Engle et al., 2020; Monasterolo, 2020). Efficiency theory focuses on reducing inputs compared to outputs. However, climate-related cost pressures can disrupt this balance, especially for banks that do not have strong climate risk management in place. Despite growing interest in climate risk in capital markets, limited research investigates how these risks affect bank-level production efficiency. This study addresses this gap by employing Data Envelopment Analysis (DEA) to measure how climate exposures influence banks' ability to convert financial and labor inputs into lending and service outputs.

Hypothesis 1: *Climate risk negatively affects bank efficiency.*

Financial derivatives are essential instruments in modern financial intermediation, enabling banks to hedge against market, credit, and environmental risks. They reduce income volatility and stabilize funding, improving banks' efficiency, especially during external shocks. Effective hedging strategies are crucial for minimizing disruptions and maintaining strong financial performance (Boubaker et al., 2020; Petersen & Thiagarajan, 2000). Although existing studies confirm that derivatives can enhance profitability or reduce risk exposure (Deng et al., 2017; Mayordomo et al., 2014), few examine their role in improving production efficiency, especially in climate risk. This study posits that financial derivatives improve risk-adjusted performance and technical efficiency.

Hypothesis 2: *Financial derivatives (both hedging and trading) positively affect bank efficiency.*

While climate risk may negatively affect efficiency and risk management, transparency mechanisms can moderate this impact. Contingency theory posits that organizational performance improves when external conditions align with internal capabilities. Derivative usage and climate disclosures are two capabilities that help banks mitigate climate-related disruptions. First, climate disclosure initiatives, particularly those aligned with the CDP and ESG frameworks, improve informational transparency, lower investor uncertainty, and facilitate strategic resource reallocation. These disclosures can act as a signaling mechanism, improving access to capital and reducing information asymmetry (Ben- Amar & McIlkenny, 2015; Depoers et al., 2016; Liesen et al., 2015). Second, financial derivative instruments tailored to climate risk—such as weather or emissions-linked contracts—can reduce exposure and operational volatility, enhancing resilience (Dewally & Shao, 2013; Lannoo & Thomadakis, 2020). Similarly, effective hedging strategies can reduce volatility and improve resilience (Vuillemey, 2019). However, the interaction between adaptive mechanisms and climate risk regarding bank efficiency remains unexplored.

Hypothesis 3: *CDP disclosure and ESG performance mitigate the negative relationship between climate risk exposure and bank efficiency.*

Hypothesis 4: *Derivative usage mitigates the negative relationship between climate risk exposure and bank efficien*cy.

This study advances the literature by proposing a hypothesis framework that links production efficiency, risk management, and climate finance. While previous research has concentrated on market-based climate risks and systemic stability (Battiston et al., 2017; Reinders et al., 2023), this study focuses on operational adaptation at the firm level. It also introduces interaction effects, demonstrating how internal strategic choices, such as hedging and disclosure, influence the efficiency impacts of external climate risks, consistent with contingency theory. Figure 1 shows the conceptual framework.

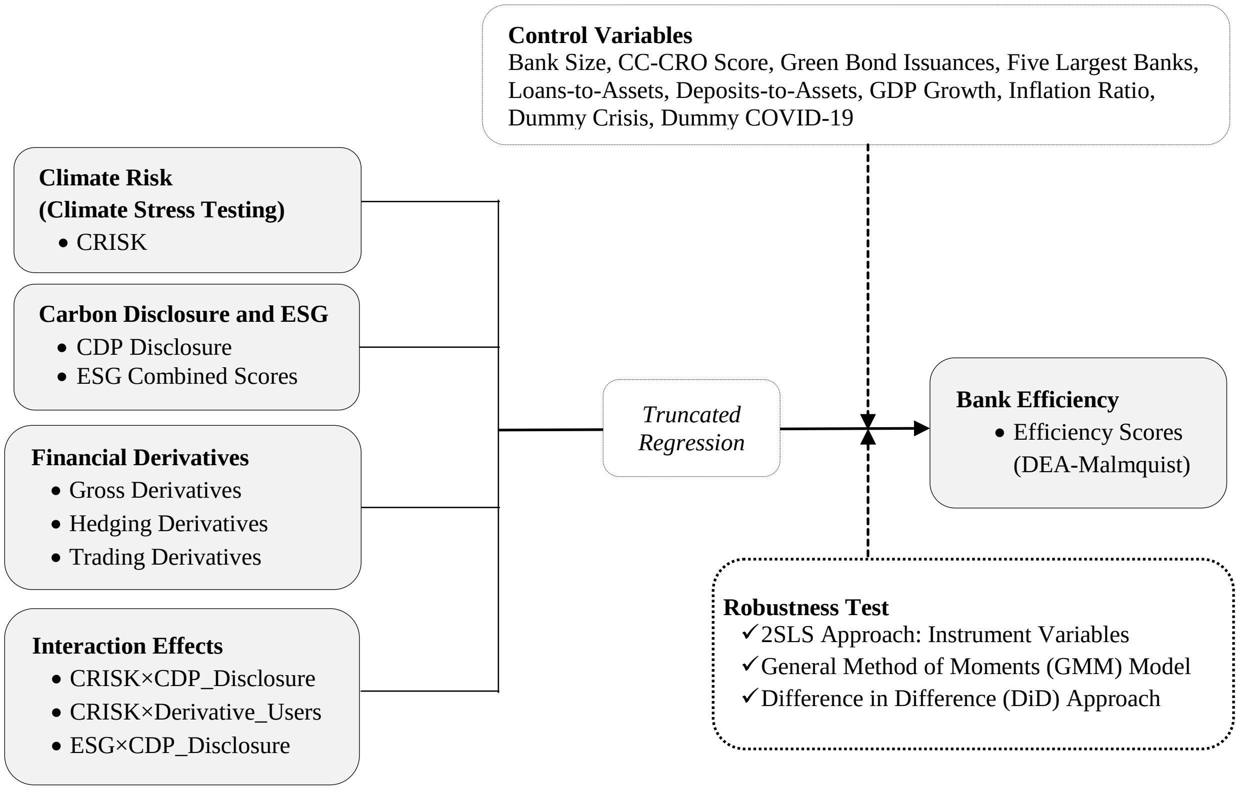

Figure 1: Conceptual framework (Chapter 4)

4. Methodology and Empirical Models

4.1 Sample selection

This study investigates publicly listed financial institutions using panel data from the Bankscope database for the period 2001 to 2021. The sample is restricted to deposit-taking institutions, specifically bank holding companies and commercial banks, to ensure comparability in business models and regulatory exposure. Non-publicly listed entities and non-bank financial institutions—including insurance companies, asset managers, and investment firms—are excluded to maintain focus on core banking operations and to ensure data availability for key financial and environmental variables. The final sample comprises 1,175 publicly traded banks across 69 countries, capturing a diverse cross-section of banking systems and regulatory environments over two decades.

4.2 Bank efficiency measures

This study uses Data Envelopment Analysis (DEA) to estimate bank-level efficiency across countries. DEA is a non-parametric method that compares the efficiency of decision-making units (DMUs) by analyzing multiple inputs and outputs without a specific functional form (Charnes et al., 1978; Farrell, 1957). This method is well-suited for the banking sector, where there can be significant variation in resources and financial service outputs, and price data may often be inconsistent or missing (Drake & Hall, 2003; Wu & Sheng, 2023). This study applies an input-oriented DEA model to align with banks' goal of minimizing resources while maintaining service output. The DEA model assesses how much a bank can reduce its inputs without compromising outputs. Extreme outliers are excluded from the analysis to ensure comparable DMUs. This study estimates efficiency scores using both the Constant Returns to Scale (CRS) model (Charnes et al., 1978) and the Variable Returns to Scale (VRS) model (Banker et al., 1984). The CRS model assumes a direct relationship between input and output growth, while the VRS model allows for return variations. The CRS model yields technical efficiency (CRSTE), and the VRS model provides pure technical efficiency (VRSPTE). Scale efficiency (SCALE) is calculated as the ratio of CRSTE to VRSPTE.

The DEA analysis treats each bank in the dataset as a DMU. The inputs include total deposits, total costs, and equity, while the outputs are total loans, non-interest income, and earning assets, following established efficiency studies. The input-oriented DEA model formulates the problem for each DMU as:

$$\begin{aligned} Min Efficiency \quad \text{subject to} \quad & Y\lambda \geq Y_i, \\ & Efficiency X \geq X\lambda, \\ & \lambda \geq 0 \end{aligned} \tag{1}$$

Here, *Efficiency* represents the efficiency score (between 0 and 1), and λ includes weights for peer DMUs. A score of 1 means the DMU is efficient, while scores below 1 indicate inefficiency. The VRS model adds the constraint ∑λ = 1, allowing for non-constant returns to scale. This dual specification facilitates a decomposition of inefficiency into pure technical and scale components.

This study implements the double-bootstrap procedure developed by Simar and Wilson (2007) to correct for bias and account for the truncated nature of DEA efficiency scores. This method provides valid inference for second-stage regression models in DEA applications, correcting for both serial correlation and the bounded distribution of efficiency scores. The estimation proceeds in the following steps:

Step 1: Calculate initial DEA efficiency scores $\widehat{Efficiency}_{ijt}$ for each bank i, in country j, and year t using Equation (4.1).

Step 2: Assemble a panel dataset of efficiency scores $\widehat{Efficiency}_{ijt}$ and associated covariates of explanatory variables Z_{ijt}, C_j, D_t, and estimate the truncated regression $Efficiency_{ijt} = \beta_0 + \beta_1 Z_{ijt} + \beta_2 C_j + \beta_3 D_t + \varepsilon_{ijt}$, where using Maximum Likelihood Estimation (MLE), $\in_{ijt} \sim N\left(0, \sigma^2\right)$ is truncated at 1.

Step 3: Perform L_1 bootstrap replications to obtain bias-corrected estimates $\hat{\beta}^{(b)}$ and $\hat{\sigma}^{(b)}$:

Simulate $\in^{*(b)} \sim N\left(0, \hat{\sigma}\right)$, truncated at $1 - \hat{\beta}_0 - \hat{\beta}_1 Z_{ijt} - \hat{\beta}_2 C_j - \hat{\beta}_3 D_t$.

Recalculate pseudo-efficiency scores $\widehat{Efficiency}_{ijt}^{*(b)}$, re-run DEA, and obtain bootstrap analogs of the inputs and outputs.

Step 4: Derive the bias-corrected efficiency scores $\widehat{\widehat{Efficiency}}_{ijt}$ by adjusting $\widehat{Efficiency}_{ijt}$ based on the estimated bias from Step 3.

Step 5: Re-estimate the truncated regression model using the bias-corrected scores and obtain updated parameter estimates $\mathring{\beta}$, $\mathring{\sigma}$.

Step 6: Conduct a second round of L_2 bootstrap replications:

Simulate new residuals $\tilde{\epsilon}^{**(b)}$ and generate double-bootstrap efficiency scores $\widehat{Efficiency}_{ijt}^{**(b)}$

Estimate the truncated regression model using $\widehat{Efficiency}_{ijt}^{**(b)}$ and obtain refined estimates $\mathring{\beta}^{(b)}$.

Step 7: Construct confidence intervals for each parameter in $\mathring{\beta}$ using the distribution of $\mathring{\beta}^{(b)}$ obtained from the double-bootstrap procedure.

4.3 Productivity change: Malmquist index based on DEA

To capture the evolution of bank productivity over time, we apply the Malmquist Productivity Index, which quantifies changes in total factor productivity (TFP) by decomposing them into two components: (i) efficiency change (TFPCH) and (ii) technological change (TECCH) (Caves et al., 1982; Färe et al., 1994). The Malmquist index is calculated using DEA frontiers estimated under an input-oriented CRS specification, enabling consistent comparison over time. The geometric mean of two period-specific productivity measures between periods t and t+1 is expressed as:

$$TFPCH = \left[\frac{D_t^t(x_{t+1}, y_{t+1})}{D_t^t(x_t, y_t)} \times \frac{D_{t+1}^{t+1}(x_{t+1}, y_{t+1})}{D_{t+1}^{t+1}(x_t, y_t)} \right]^{\frac{1}{2}} \qquad (2)$$

Where D_t^t and D_{t+1}^{t+1} are distance functions at time t and t+1, respectively. A value of TFPCH > 1 indicates productivity improvement, while values below 1 reflect deterioration. This index allows us to distinguish whether performance shifts stem from better input utilization (TFPCH) or technological progress (TECCH). Given the importance of operational and technological adaptations in banking under climate and regulatory pressures, this decomposition provides critical insights into drivers of bank productivity dynamics.

4.4 Climate risk measurement methodologies

According to the Bank for International Settlements (BIS), the effectiveness of climate risk measures depends largely on the quality and consistency of data, the rigor of scenario analyses, and the adaptability of methodologies across diverse industries and jurisdictions (BIS, 2021). For a comparison of the climate risk measures. First, climate stress testing and climate Value at Risk (VaR) enable financial institutions to identify systemic risks. However, they are limited by scenario dependency and the ongoing evolution of climate models. Second, accounting for carbon emissions is vital for corporate sustainability, but the challenges associated with Scope 3 emissions underscore the urgent need for improved data collection and reporting mechanisms. Third, ESG risk ratings and transition risk analyses offer essential insights into climate-related financial threats, though they suffer from methodological inconsistencies and regulatory uncertainties. Furthermore, physical climate risk assessments are crucial for urban planning and insurance pricing, as they significantly impact infrastructure and asset resilience. Nevertheless, reliance on high-resolution climate projections remains a considerable constraint. As regulatory frameworks advance, the urgency for greater standardization and methodological enhancements in climate risk assessment becomes increasingly critical for informed decision-making in both financial and policy scenarios.

This study advocates for climate stress testing as the foundational methodology for evaluating climate risk, highlighting its essential role in assessing the resilience of the financial system to climate-related shocks. Climate stress testing provides a structured, scenario-based framework that enables financial institutions, policymakers, and regulators to quantify potential economic and financial disruptions arising from both physical and transition risks. Importantly, unlike traditional climate risk metrics that concentrate on isolated environmental or corporate sustainability factors, such as ESG performance and carbon emissions accounting, climate stress testing offers a holistic assessment of system-wide financial vulnerabilities. Given the increasing acknowledgment of climate risks within financial stability frameworks, as highlighted by BIS (2021), climate stress testing adopts a macroprudential perspective, making it particularly relevant for central banks, regulators, and financial institutions. Furthermore, climate stress testing utilizes forward-looking scenario analysis, equipping institutions with the necessary tools to evaluate how financial portfolios and economic sectors might perform under a range of climate-related stress conditions, as noted by NGFS (2020). This proactive approach stands in stark contrast to static assessments, such as carbon emissions accounting, which only track historical and current emissions without explicitly modeling their financial implications.

Moreover, international financial regulatory bodies—including the European Central Bank, the Bank of England, and the Federal Reserve—are increasingly adopting climate stress testing to integrate climate risk into capital adequacy assessments and broader financial risk frameworks, as highlighted by IMF (2020a). This approach aligns with regulatory priorities, making it a practical and policy-relevant tool for addressing climate-related financial stability challenges. In contrast to ESG risk ratings, which often lack the necessary standardization and transparency for effective decision-making, as noted by Hain et al. (2022), climate stress testing provides quantifiable financial estimates of potential losses across a range of climate risk scenarios. This equips decision-makers with the ability to evaluate risk exposure, assess capital adequacy, and measure portfolio resilience, establishing it as a strong resource for both financial institutions and policymakers. Furthermore, while many current climate risk measures focus solely on physical risks (such as physical risk assessments) or transition risks (like transition risk analysis), climate stress testing distinguishes itself by incorporating both dimensions. This comprehensive risk assessment across financial portfolios and economic sectors (BIS, 2021) is particularly beneficial given the uncertainties surrounding climate policies, carbon pricing, and extreme weather trends. Past studies have emphasized the crucial role of climate stress testing in evaluating climate risk (Acharya et al., 2023; Battiston et al., 2021; Battiston et al., 2017; Pantos, 2023; Reinders et al., 2023). Institutions such as the Network for Greening the Financial System (NGFS) and Bank for International Settlements (BIS) have actively endorsed its implementation, further enhancing its credibility and significance.

In summary, as demand for resilience in the financial system increases, climate stress testing is a vital approach that meets stricter regulatory standards and provides better assessments of climate risk. Its scenario-driven analysis and quantifiable impacts make it essential for assessing systemic climate risks. In order to effectively address climate adaptation and mitigation, regulators, financial institutions, and policymakers must integrate climate stress testing into their risk assessment frameworks.

Climate risk (CRISK) measures the climate-related risks faced by global banks. According to Jung et al. (2022), CRISK is assessed through a three-step climate stress testing process. The first step involves measuring the climate risk factor, focusing on transition risk as indicated by the stranded asset (SA) portfolio. This portfolio, formed using Litterman's method, includes 30% in the energy ETF (XLE), 70% in the coal ETF (KOL), and a short position in the MSCI All-Country World Index (ACWI) to represent the market. The underperformance of this SA portfolio is an indicator of increasing transition risks.

The second step estimates the time-varying climate betas for banks employing the Dynamic Conditional Beta (DCB) model. MKT_{it} is the market return and CF_{it} is the climate risk factor obtained from the previous step. β_{it}^{Mkt} is the market beta and $\beta_{it}^{Climate}$ is the climate beta. The stock return (r_{it}) of bank i at time t is modeled as:

$$r_{it} = \beta_{it}^{Mkt} MKT_t + \beta_{it}^{Climate} CF_t + \varepsilon_{it}, \tag{3}$$

The third step is to compute CRISK, as outlined by Acharya et al. (2012) and Brownlees and Engle (2017). CRISK represents the expected capital shortfall under climate stress conditions and is determined as follows:

$$CRISK_{it} = kD_{it} - (1-k) W_{it} (1 - LRMES_{it}), \tag{4}$$

Where *D* denotes the bank's book debt, *W* symbolizes the bank's market value, and *LRMES* stands for the long-run marginal expected shortfall, which indicates the expected proportional loss of the bank's equity if the SA portfolio undergoes a substantial decline within six months. It is computed as:

$$LRMES = 1 - \exp\left[\beta^{Climate} \log(1-\theta)\right], \tag{5}$$

Where θ denotes the climate stress level, with a default setting of 50%. *k* represents a prudent capital level expressed as a portion of assets.

Marginal CRISK refers to the difference between CRISK under the current climate stress and CRISK without any climate stress, wherein the non-stressed CRISK indicates a capital deficiency in the absence of climate stress. It assesses the impact of climate stress after accounting for the existing capital shortfall. It can be expressed as:

$$Marginal\ CRISK = (1-k) W\ LRMES, \tag{6}$$

CRISK can be decomposed into three components:

$$\Delta CRISK = k\Delta D - (1-k)(1-LRMES)\Delta W + (1-k) W \Delta LRMES, \tag{7}$$

Where $dDEBT = k\Delta D$ is the contribution of the firm's debt to CRISK. $dEQUITY = -(1-k)(1-LRMES)\Delta W$ is the effect of the firm's equity position on CRISK. $dRISK = (1-k)\,W\Delta LRMES$ is the contribution of an increase in volatility or correlation to CRISK. It reflects the changes in climate beta.

4.5 Two-stage DEA approach

Following the estimation of DEA efficiency scores, the second stage evaluates how external factors influence bank efficiency. We adopt a two-stage DEA methodology, where DEA scores obtained in Stage 1 serve as the dependent variable in a truncated regression model in Stage 2. This approach addresses the bounded nature of E(0,1) of DEA scores and corrects for serial correlation and estimation bias (Simar & Wilson, 2007, 2011). While traditional methods such as OLS or Tobit models have been used in second-stage DEA (Hoff, 2007; McDonald, 2009), they often yield biased results due to inappropriate distributional assumptions and neglect of the scores' estimated nature (Barros & Assaf, 2009). Simar and Wilson (2007) propose a double-bootstrap truncated regression framework that overcomes these limitations by simulating the data-generating process and correcting for bias in both the efficiency estimates and the regression parameters. The second-stage truncated regression model is specified as follows:

Baseline regression:

$$\begin{aligned}(\text{Efficiency})_{ijt} = {} & \beta_0 + \beta_1(\text{CRISK})_{ijt} + \beta_2(\text{CDP Disclosure})_{ijt} + \beta_3(\text{Financial Derivatives})_{ijt} \\ & + \beta_4(\text{ESG Performance})_{ijt} + \gamma(\text{Bank-level Controls})_{ijt} \\ & + \delta(\text{Country-level Controls})_{jt} + \mu(\text{Economic Shocks})_t + \pi_{ijt} + \varepsilon_{ijt}, \end{aligned} \tag{8}$$

Baseline regression with interaction effects (including CRISK×CDP_Disclosure, CRISK×Derivative_Users, and ESG×CDP_Disclosure):

$$\begin{aligned}(\text{Efficiency})_{ijt} = {} & \beta_0 + \beta_1(\text{CRISK})_{ijt} + \beta_2(\text{CDP Disclosure})_{ijt} + \beta_3(\text{Financial Derivatives})_{ijt} \\ & + \beta_4(\text{ESG Performance})_{ijt} + \beta_5(\text{Interaction Effects})_{ijt} + \gamma(\text{Bank-level Controls})_{ijt} \\ & + \delta(\text{Country-level Controls})_{jt} + \mu(\text{Economic Shocks})_t + \pi_{ijt} + \varepsilon_{ijt}, \end{aligned} \tag{9}$$

Where the subscripts *i*, *j*, and *t* signify the bank *i* in the country *j* at time *t*. Financial derivatives include gross derivatives, hedging derivatives, and trading derivatives. Bank-level controls include TCFD member, PRB member, CC-CRO score, bank size, loans-to-assets, and deposits-to-assets. Country-level controls include green bond issuances, the five largest banks, GDP growth, and inflation ratio. Economic shocks include dummy crisis and dummy COVID-19. π represents fixed effects, including bank, country, and time-fixed effects. ε is the truncated error term clustering by bank, country, and year, which are adjusted for heteroscedasticity, cross-sectional correlation, and serial correlation (Petersen, 2009). The definition of all variables is shown in Table 1.

[Insert Table 1 here]

5. Empirical Results

5.1 Descriptive statistics

Table 2 presents the descriptive statistics for the full sample, comprising 14,970 bank-year observations. The table reports mean, standard deviation, minimum, and maximum values for each variable, capturing both central tendencies and the degree of dispersion within the dataset. Bank efficiency is estimated using the DEA-Malmquist index, employing three input variables—total deposits, total equity, and total cost—and three output variables—total loans, non-interest income, and other earning assets. On average, banks hold total deposits of USD 46.361 billion, with a notably high standard deviation (USD 190.864 billion), reflecting considerable heterogeneity in bank size and funding capacity. Similarly, the mean value of total loans is USD 46.939 billion, reflecting a wide dispersion in lending practices and risk exposure across banks. Climate risk—CRISK—exhibits a mean value of USD 4.985 billion and ranges from near zero to USD 90 billion, indicating diverse exposures to climate stress across banks. This wide range underscores the heterogeneity in climate risk exposure, consistent with findings from previous studies emphasizing regional and sectoral disparities in climate vulnerability (Battiston et al., 2017; Monasterolo, 2020). Notably, only 16.4% of banks in the sample disclose carbon-related information, underscoring a general lack of transparency in climate risk reporting.

Banks' engagement with financial derivative instruments also varies widely. The average gross notional value of derivatives is USD 16.100 billion, although the high standard deviation reflects skewed usage patterns driven by a small number of highly active institutions. Hedging derivatives average USD 0.727 billion, while trading derivatives average USD 15.400 billion. This disparity implies that most derivative use is geared toward speculative trading rather than hedging, aligning with Vuillemey (2019) and Chen and Phan (2024). Regarding ESG performance, the average ESG combined score is 0.435, with a standard deviation of 0.224. This variability points to divergent levels of ESG integration across banks, which may have implications for financial resilience and operational efficiency. Several control variables provide additional insights into institutional structures and risk profiles. Bank size, measured as the natural logarithm of total assets, averages 20.514, while key financial ratios such as loans-to-assets (mean = 0.511), and deposits-to-assets (mean = 0.528) provide insights into balance sheet composition and risk exposure. At the country level, the logarithm of green bond issuances is a proxy for national climate finance activity, with a mean value of 0.332. Market concentration, measured by the asset share of the five largest banks, averages 0.600, indicating moderately concentrated banking systems. Macroeconomic conditions are reflected in average GDP growth (2.5%) and inflation (3.0%), offering additional context for cross-country comparisons in financial and climate resilience.

[Insert Table 2 here]

5.2 Cross-country banking efficiency

Table 3 offers a cross-country comparison of banking efficiency, calculated using the DEA-Malmquist approach. Three efficiency metrics—CRSTE, VRSTE, and SCALE—are reported, providing a nuanced view of banks' ability to convert resources into outputs under different operational conditions. The variation in efficiency scores across countries is substantial. High-performing countries, such as Kazakhstan (CRSTE = 0.9743; SCALE = 0.9845), Pakistan (CRSTE = 0.9637; SCALE = 0.9874), and Poland (CRSTE = 0.9629; SCALE = 0.9939), demonstrate high levels of technical and scale efficiency. These results are consistent with previous research (Fukuyama & Weber, 2010), which suggests that moderately sized banking systems with effective regulatory frameworks tend to achieve superior efficiency outcomes. However, countries like Puerto Rico (CRSTE = 0.3712) and Qatar (CRSTE = 0.4434) report much lower efficiency, pointing to potential institutional inefficiencies, inadequate risk management frameworks, or market distortions. Despite Puerto Rico's low CRSTE, its relatively high scale efficiency (SCALE = 0.9655) suggests that the issue lies in operational inefficiencies rather than size-related challenges. This finding supports Barros and Assaf (2009), who argue that inefficiencies are often process-related rather than purely due to market size.

Interestingly, developed economies such as the United States (CRSTE = 0.9051) and the United Kingdom (CRSTE = 0.8794) exhibit moderate efficiency scores, which may be attributed to the complexities of large banking institutions and burdensome regulatory requirements. This observation aligns with Pasiouras (2008), who found that banks in advanced economies do not consistently outperform their counterparts in emerging markets. Emerging economies like India (CRSTE = 0.8699) and Brazil (CRSTE = 0.9214) demonstrate relatively high efficiency, reflecting the positive effects of financial reforms and digital banking innovations. However, countries with strong ESG or climate finance frameworks—such as Sweden (CRSTE = 0.9053), Germany (CRSTE = 0.8675), and France (CRSTE =

0.8676)—exhibit only moderate efficiency levels. This suggests that the operational costs associated with ESG compliance and climate risk mitigation, particularly in the early stages of implementation, may temporarily reduce short-term efficiency. On average, banks show higher efficiency under variable returns to scale (VRSTE) compared to constant returns to scale (CRSTE), suggesting that, while banks perform efficiently relative to their peers, they face challenges in achieving optimal performance when scale efficiency is strictly constrained. These findings echo Kamarudin et al. (2017), who emphasize the importance of regulatory and contextual factors in shaping efficiency outcomes.

[Insert Table 3 here]

Table 4 presents the TFPCH estimates for banks across 69 countries, decomposing productivity growth into three components: technical efficiency change—TECH, technical change—TECCH, and scale efficiency change—SECH. On average, TFPCH values exceed 1, suggesting overall positive productivity growth in the global banking sector, albeit with considerable cross-country variation. Countries such as Russia (TFPCH = 1.1236), Egypt (1.1119), and Canada (1.0866) exhibit the highest levels of productivity growth, primarily driven by significant technological advancements. Russia’s TECH score of 1.1289, in particular, reflects substantial innovation and the integration of digital banking and fintech solutions. These findings are consistent with Lin and Zhang (2009) and Chen et al. (2022), who emphasize the role of technological catch-up in enhancing productivity, especially in emerging markets. Conversely, countries like Puerto Rico (TFPCH = 0.9995) and Iceland (0.9972) demonstrate minimal or no productivity growth. In these cases, any gains in TECCH appear to be offset by stagnation in technological progress. This observation supports that smaller or less dynamic banking markets have difficulty improving productivity without significant innovation (Fukuyama & Matousek, 2011).

Across most countries, TECCH scores fall below 1, indicating suboptimal utilization of available technologies. Despite advancements in digital banking and artificial intelligence, banks are not fully realizing the potential efficiency gains. This pattern echoes the arguments of Berg et al. (1992) and Delis and Kouretas (2011), who attribute lags in efficiency improvements to institutional rigidities and managerial inefficiencies. Notably, countries such as Nigeria (SECH = 1.0200) and Kenya (1.0068) display significant improvements in scale efficiency, suggesting that banks in these markets have become more effective in adjusting their operational scale. These results may reflect the impact of market consolidation or regulatory reforms, supporting the findings of Casu et al. (2013), who note that financial restructuring in emerging markets can lead to meaningful scale efficiency gains. High-income countries such as Australia (TFPCH = 1.0487), Japan (1.0356), and Singapore (1.0461) also show notable productivity growth, primarily driven by technological change rather than efficiency improvements. This finding is consistent with Koutsomanoli-Filippaki et al. (2012), who suggest that in advanced financial systems, TFPCH gains are largely a result of continuous innovation rather than substantial efficiency enhancements. In summary, technological advancement emerges as the predominant driver of productivity growth in the global banking sector. However, the underutilization of these innovations in terms of technical efficiency highlights a critical area for improvement across both emerging and developed economies.

[Insert Table 4 here]

Table 5 provides a longitudinal analysis of global banking productivity from 2001 to 2021. Panel A reveals that the long-term average for CRSTE is 0.8998, suggesting that banks, on average, operated at 89.98% efficiency relative to the best-practice frontier. The corresponding mean values for VRSTE and SCALE are 0.9351 and 0.9595, respectively—indicating relatively high, yet imperfect, efficiency levels. The findings highlight persistent inefficiencies due to poor input-output processes and problems with scaling. The period immediately following the 2008 global financial crisis (2009–2012) demonstrates a gradual recovery in CRSTE and VRSTE, reflective of sector-wide restructuring initiatives and governance enhancements. In 2015, CRSTE reached a notable peak of 0.9166 due to the implementation of Basel III and improved risk management standards. From 2016 onwards, a renewed decline is evident, with CRSTE falling to 0.8990 by 2021—likely a consequence of the COVID-19 pandemic and associated operational disruptions. Baltas et al. (2022) highlight that exogenous shocks negatively impact banking efficiency, especially in areas with poor digital infrastructure or low capital reserves.

Panel B presents evidence of modest but sustained productivity growth over the sample period, with an average TFPCH of 1.0360. The productivity gain is mainly due to TECH, which averaged 1.0601, while TECCH is lower at 0.9839. Despite advancements in technology, banks have had difficulty fully leveraging these innovations. For instance, in 2004–2005, TFPCH surged to 1.2134, driven by an exceptional increase in TECH (1.3122), yet TECCH declined to 0.9003, highlighting inefficiencies in adapting to rapid technological progress. The post-crisis recovery years of 2008–2009 and 2009–2010 saw heightened TECCH (1.0568 and 0.7585, respectively), with the latter period experiencing a significant spike in TECH (1.4497), potentially indicative of structural technological overhauls. In contrast, the pandemic period (2020–2021) witnessed a decline in TFPCH (0.9822) and TECCH (0.9815), suggesting that banks faced difficulties in maintaining productivity amid widespread disruption. Although TECH remained marginally above unity (1.0127), it was insufficient to compensate for efficiency losses.

These findings affirm a well-established theme in the banking efficiency literature: while technological advancement remains the principal driver of productivity improvements, its potential is often undercut by a lag in operational and managerial adaptation. Berger and Humphrey (1997) highlight the need for banks to align their internal capabilities and regulatory frameworks with technological advancements to achieve maximum productivity. The stable Scale Efficiency Change (SECH ≈ 1.0025) indicates that banks are generally operating at appropriate scales for their market conditions. However, ongoing inefficiencies in CRSTE and TECCH reveal the critical need for strong management, effective risk governance, and rigorous cost control. These insights echo the work of Altunbas et al. (2007), who stress that differences in strategic focus and governance quality significantly influence bank efficiency. In conclusion, Table 5 illustrates a nuanced picture of global banking productivity over two decades—characterized by steady technological progress tempered by structural and cyclical inefficiencies. These results highlight the critical importance of pairing technological investments with institutional strengthening, adaptive managerial practices, and responsive regulatory oversight—core imperatives echoed throughout the contemporary banking efficiency literature.

[Insert Table 5 here]

5.3 Truncated regression results

Table 6 presents the results from truncated regression models that explore the nuanced interplay between climate risk, climate-related disclosures, and bank efficiency. The analysis distinguishes between two dimensions of efficiency: technical efficiency (CRSTE, columns 1–3) and pure technical efficiency (VRSTE, columns 4–6). A robust and consistent pattern emerges across all specifications that climate risk (CRISK) is negatively and significantly associated with both efficiency measures. This finding supports hypothesis 1, suggesting that climate risk imposes additional operational or compliance burdens on banks. Climate risk imposes a measurable drag on bank efficiency, plausibly driven by increased regulatory uncertainty, the prospect of stranded assets, and rising reputational risks. These results align with Feng et al. (2024), highlighting the disruptive impact of climate risk on financial performance. Conversely, CDP disclosure exerts a positive and statistically significant influence on efficiency. The results show that banks engaging in more transparent climate-related reporting exhibit an increase in CRSTE and VRSTE. These findings are consistent with Amel-Zadeh and Serafeim (2018), reinforcing the argument that climate transparency enhances stakeholder confidence and risk management practices, thereby improving operational efficiency.

The role of derivatives—both in aggregate and disaggregated by function—emerges as another critical dimension. Gross derivatives usage and its components (hedging and trading derivatives) are positively and significantly associated with both efficiency measures. The strongest effects are observed for hedging derivatives, with coefficients of 0.0226 (CRSTE) and 0.0263 (VRSTE), suggesting that strategic risk management through hedging plays a pivotal role in shielding banks from climate-induced volatility, ultimately supporting efficiency improvements. This result is consistent with Hypothesis 2, suggesting that derivatives, particularly those used for hedging and trading, may enhance operational efficiency by mitigating risk and optimizing asset-liability management (Casu & Molyneux, 2003).

The findings regarding ESG performance (ESG combined score) are more mixed. While models (1) and (2) suggest a positive relationship with CRSTE, this effect diminishes and becomes statistically insignificant in model (3) and across all VRSTE specifications. This result demonstrates that ESG scores may offer less insight into efficiency outcomes when compared to targeted carbon disclosure. Furthermore, the CC-CRO score, which reflects the quality of climate governance, reveals a significant negative relationship with CRSTE in models (2) and (3) but does not show significance in the VRSTE models. This unexpected outcome may be attributable to delays in the implementation of governance reforms or inconsistencies in climate oversight across various institutions. The impact of green bond issuance is limited to profit efficiency, with significant positive coefficients in the VRSTE models. This suggests that while green financing initiatives may not immediately affect technical efficiency, they may contribute to longer-term improvements in managerial efficiency or profitability.

Among control variables, bank size, loan intensity (loans-to-assets), and funding structure (deposits-to-Assets) are positively and significantly associated with efficiency, particularly for VRSTE. These results align with prior literature suggesting that scale and balance sheet composition influence operational performance (Berger & Humphrey, 1997). Interestingly, GDP growth exhibits opposite effects—positively related to CRSTE but negatively to VRSTE—highlighting the differentiated response of efficiency metrics to macroeconomic conditions. Additionally, both inflation and the COVID-19 pandemic dummy are associated with significant efficiency losses across all models, emphasizing the adverse effects of macroeconomic uncertainty and systemic crises on banking performance. In sum, the results underscore the dual threats and opportunities presented by climate-related factors. While climate risk erodes bank efficiency, institutions that proactively disclose climate information and utilize financial instruments such as derivatives—particularly for hedging—are better positioned to sustain performance. These findings highlight the strategic importance of integrating climate risk management into core banking operations in an increasingly uncertain environmental landscape.

[Insert Table 6 here]

Table 7 illustrates the findings from truncated regression models incorporating interaction terms to assess the moderating effects of CDP disclosure and ESG performance on the relationship between climate risk and bank efficiency. The coefficient on the lagged dependent variable remains positive and highly significant across all model specifications, indicating strong persistence in bank efficiency over time. CRISK consistently shows a negative and statistically significant relationship with both CRSTE and VRSTE. This consistent finding affirms Hypothesis 1, suggesting that higher exposure to climate risk systematically undermines bank operational performance. Furthermore, this table reinforces empirical support for Hypothesis 2, where the coefficient on hedging derivatives remains positive and highly significant. These findings indicate that derivative usage—particularly for hedging purposes—acts as a strategic instrument to buffer against climate-induced volatility and enhance efficiency outcomes.

Notably, the interaction between CRISK and CDP disclosure (CRISK×CDP_Disclosure) reveals a significant moderating effect. Across all CRSTE models, this interaction term is positive and statistically significant, indicating that climate-related disclosures help attenuate the adverse impact of climate risk on technical efficiency. Although the interaction is statistically insignificant in the VRSTE models, the positive sign of the coefficients suggests a directionally consistent effect. This divergence implies that transparent climate disclosures primarily enhance the efficient allocation and utilization of resources—captured by CRSTE—rather than managerial efficiency. These findings support Hypothesis 3, highlighting the role of credible and transparent disclosure practices in fostering resilience and enhancing stakeholder confidence, thus mitigating the efficiency penalties associated with elevated climate risk. Similarly, the interaction between ESG performance and CDP disclosure (ESG×CDP_Disclosure) yields consistently positive and statistically significant coefficients across both efficiency measures. This result suggests that the positive impact of ESG engagement on bank efficiency is magnified when supported by robust and credible disclosure practices, aligning with (Eccles & Krzus, 2018). Put differently, disclosure acts as a signal that enhances the effectiveness and credibility of broader sustainability initiatives, thereby amplifying their operational benefits. The interaction between CRISK and derivative usage is positive and statistically significant across all model specifications (Columns 1–6). These results provide strong support for hypothesis 4, emphasizing that banks using derivatives are better equipped to buffer the efficiency losses driven by climate risk. In sum, the results underscore the strategic value of integrating carbon disclosure with ESG frameworks. Climate risk reduces bank efficiency, but transparency through disclosure, especially when linked to strong ESG performance, can lessen these effects. This highlights the importance of adopting clear and effective sustainability strategies to improve bank resilience in the face of climate challenges.

[Insert Table 7 here]

5.4 Addressing endogeneity issues

Table 8 addresses potential endogeneity concerns by employing instrumental variables (IV) within a two-stage least squares (2SLS) framework. In the first stage, the instruments used—TCFD membership and PRB membership—serve to predict CDP disclosure. The results indicate that both instruments are strong predictors: TCFD membership has a coefficient of 0.0315 ($p < 0.01$), and PRB membership has a notably higher coefficient of 0.1141 ($p < 0.01$). These results suggest that increased memberships in TCFD and PRB correlate with enhanced climate-related disclosures, providing strong support for the use of these instruments in mitigating potential endogeneity issues. In the second stage of the 2SLS approach, we replace CDP disclosure with its predicted values from the first stage. The results reveal that the coefficient for climate risk (CRISK) changes from 0.006 ($p < 0.01$) in the first stage to -0.0012 ($p < 0.01$) in the second stage. This shift indicates that controlling for endogeneity slightly reduces the negative impact of climate risk on CRSTE outcomes, reinforcing the hypothesis that higher climate risk erodes bank efficiency, but that this relationship may be overstated in the presence of endogenous disclosure choices. The lagged dependent variable remains strongly significant, with a coefficient of 2.1959 ($p < 0.01$), emphasizing the persistence of bank efficiency over time. In terms of derivatives usage, the coefficient for gross derivatives increases from 0.0037 ($p < 0.05$) in the first stage to 0.0043 ($p < 0.01$) in the second stage, suggesting that the positive effect of derivative usage on CRSTE becomes even more pronounced when endogeneity is controlled for. These findings reaffirm the importance of derivatives as a strategic tool for managing risk and enhancing bank efficiency, particularly when addressing climate-induced volatility.

[Insert Table 8 here]

Table 9 presents key diagnostic tests that confirm the strength of our instruments and the robustness of the model. The Kleibergen-Paap LM test reports a chi-square statistic of 106.03 ($p = 0.0000$), confirming model identification and instrument relevance. The Cragg-Donald F-statistic of 70.62 exceeds the Stock-Yogo critical value of 19.93, indicating that the instruments are strong. Similarly, the Kleibergen-Paap rk Wald F-statistic of 53.99 affirms robustness under heteroskedasticity, while the Stock-Yogo weak ID test further validates instrument strength, with the Cragg-Donald statistic comfortably above the critical threshold. The Hansen J test yields a chi-square of 0.061 ($p = 0.8044$), suggesting no overidentification issues and supporting the validity of the instruments. The Durbin-Wu-Hausman test ($\chi^2 = 19.17$, $p = 0.0000$) confirms the endogeneity of CDP Disclosure, reinforcing the need for instrumental variable estimation. In addition, both the Anderson-Rubin F-test ($F = 11.05$, $p = 0.0000$) and the Wald chi-square test ($\chi^2 = 22.13$, $p = 0.0000$) demonstrate that the instruments reliably estimate the endogenous regressor. The Stock-Wright LM S test ($\chi^2 = 26.02$, $p = 0.0000$) further supports model robustness under weak identification. The model exhibits a strong overall fit, with an F-statistic of 53.99 ($p = 0.0000$) and an R-squared of 0.673, indicating that it explains 67.3% of the variance in the dependent variable. A low RMSE of 0.065 highlights the model's predictive accuracy. In sum, these diagnostic tests confirm that the instruments are strong, valid, and well-suited to address endogeneity in CDP disclosure, reinforcing the overall reliability of the model.

[Insert Table 9 here]

Table 10 presents findings from the robustness test using the GMM approach, highlighting the relationship between key variables and banking efficiency. Consistent with the main findings, the GMM results confirm that climate risk has a significant negative impact on efficiency, underscoring the operational challenges posed by climate-related exposures. However, the results also reaffirm the crucial mitigating roles of CDP disclosures and strategic use of derivatives. Banks that actively disclose climate risks and engage in derivatives trading—particularly for hedging purposes—tend to exhibit higher efficiency levels. Moreover, the interaction terms reveal that combining climate risk management with strong ESG performance and transparent disclosure practices further enhances efficiency. This result reinforces that banks with integrated and forward-looking climate strategies are better positioned to manage emerging environmental risks. Overall, the findings highlight the importance of adopting robust climate disclosure practices, leveraging derivatives strategically, and strengthening ESG frameworks to boost operational efficiency and institutional resilience amid rising climate-related uncertainties.

[Insert Table 10 here]

Table 11 presents findings from a difference-in-differences (DiD) regression analysis that examines the average treatment effect on the treated (ATET) among banks engaged in different categories of derivatives usage. The results indicate that banks participating in derivative trading, particularly those involved in speculative activities, experience significant improvements in banking efficiency. This positive impact is evident across both CRSTE and VRSTE, highlighting the efficiency-enhancing role of derivative strategies in managing financial risk. Moreover, strong ESG performance and comprehensive climate-related disclosures improve efficiency, particularly in managing climate risks. This result underscores the crucial role that derivative strategies and climate management practices play in enhancing the operational effectiveness of financial institutions. Banks can better manage financial and non-financial risks by integrating strong climate risk management with ESG frameworks, improving operational efficiency.

[Insert Table 11 here]

6. Discussion and Implications

6.1 Discussion

The findings presented in Tables 6 and 7 contribute to and extend the growing literature on the intersection of climate risk and bank efficiency, extending empirical evidence regarding how climate risk (CRISK) influences operational performance within the banking sector. The negative relationship between climate risk and both technical (CRSTE) and pure technical efficiency (VRSTE) robustly supports Hypothesis 1. These results align with the work of Battiston et al. (2017), who highlight that climate risk introduces balance sheet fragility through factors such as asset stranding, reputational damage, and regulatory uncertainty. Our findings reinforce this view by showing that higher CRISK scores systematically reduce bank efficiency, indicating that climate-related risks impede effective resource allocation and compromise managerial effectiveness.

The positive relationship observed between derivative usage (particularly hedging derivatives) and bank efficiency metrics further confirms Hypothesis 2, supporting previous literature that emphasizes the crucial role of risk management tools in enhancing bank efficiency. In line with Bartram et al. (2011), our results demonstrate that derivative use, especially for hedging purposes, serves as a key strategy for managing downside risks, particularly when faced with heightened environmental uncertainty. The magnitude of the coefficient on hedging derivatives, especially in CRSTE models, suggests that these financial instruments not only mitigate short-term volatility but also provide a stabilizing effect that strengthens long-term operational resilience.

A noteworthy contribution of our study is the identification of the moderating role of climate-related disclosures. The significant interaction between climate risk (CRISK) and CDP disclosure (CRISK×CDP_Disclosure) reveals that greater transparency in climate-related disclosures significantly reduces the negative impact of climate risk on efficiency, supporting Hypothesis 3. This finding complements and extends earlier studies by Krueger et al. (2020) and Ilhan et al. (2021), who argue that climate transparency fosters trust, reduces information asymmetries, and enhances a firm's ability to secure financing under risk. Our study suggests that disclosure practices not only improve market perception but also contribute to tangible operational outcomes by reducing the efficiency losses associated with exposure to climate risks.

Moreover, the interaction effects between CRISK and financial derivatives underscore the combined benefits of disclosure and risk management. While derivatives help mitigate financial volatility, they also alleviate the structural challenges posed by climate-related exposures, thus reinforcing the impact of Hypothesis 4. Both climate transparency and active risk management through derivatives appear to work synergistically, supporting the sustained performance of banks under climate stress. These dual strategies suggest that banks can better manage climate-related vulnerabilities by adopting both disclosure practices and financial hedging mechanisms. The positive interaction between ESG performance and CDP disclosure highlights that transparency amplifies the benefits of broader sustainability strategies. This is consistent with Cheng et al. (2014) and Ferriani and Natoli (2021), who contend that ESG disclosures enhance the credibility and signaling value of sustainability commitments. However, the limited or statistically insignificant effects of ESG performance alone, especially in VRSTE models, warrant further discussion. This contrasts with previous studies (Gangi et al., 2019; Nofsinger & Varma, 2014) that report positive links between ESG performance and efficiency, but aligns with more recent critiques (Berger et al., 2022) which highlight the inconsistency and limited comparability in ESG ratings. Our findings suggest that the impact of ESG performance is conditional on the quality of disclosures, indicating that ESG metrics are more effective when integrated within transparent, verifiable frameworks.

6.2 Implications

Theoretical implications. This study advances theoretical understanding by integrating environmental risk exposure, ESG performance, and disclosure practices within a unified empirical framework. The significant negative relationship between climate risk (CRISK) and bank efficiency provides strong empirical support for theoretical models that link environmental stress to operational inefficiencies (as discussed by Battiston et al. (2017)). By indicating that CDP disclosure moderates the negative effects of climate risk, we contribute to signaling theory and stakeholder theory, suggesting that transparency serves not only as a communication tool but also as a mechanism for enhancing institutional resilience in the face of environmental risks. Moreover, the interaction between ESG performance and disclosure highlights the complementarity of internal sustainability efforts and external transparency. This offers a refined perspective on the channels through which ESG strategies influence firm-level performance, emphasizing that these strategies should not be viewed in isolation but as complementary mechanisms that work together to improve operational performance.

Practical implications. This study offers banking professionals and sustainability managers key insights on managing climate risk and enhancing efficiency. Banks that face significant climate risks may encounter operational inefficiencies unless they actively manage and disclose these risks. The positive effects of derivative usage, particularly in hedging against climate-related volatility, suggest that integrating climate risk considerations into financial risk management frameworks can yield measurable performance benefits. Furthermore, banks that combine strong ESG performance with credible disclosure mechanisms are better positioned to sustain efficiency under climate stress. This underscores the importance of embedding ESG and disclosure strategies into the core operations and governance structures of banks, rather than treating them as peripheral or symbolic efforts.

Policy implications. From a regulatory perspective, the study's findings highlight the importance of robust and standardized climate disclosure frameworks. The mitigating role of CDP disclosure in the climate risk-efficiency relationship lends empirical support to global initiatives such as the CDP, TCFD, and the International Sustainability Standards Board (ISSB). Regulators and policymakers should encourage or mandate disclosure practices that are verifiable, comparable, and linked to strategic risk management, particularly within the banking sector. In addition, financial authorities might consider incentivizing the use of climate-related hedging instruments and integrating climate risk stress testing into supervisory reviews. These policy measures can enhance the resilience of the financial system by aligning institutional behavior with long-term climate goals and risk-aware governance.

7. Conclusion, Limitations, and Future Research

This study provides novel insights into the relationship between climate risk, disclosure practices, and bank efficiency, utilizing truncated regression models on an extensive panel of international banks. The findings confirm that heightened exposure to climate risk significantly impairs both technical efficiency (CRSTE) and managerial efficiency (VRSTE), highlighting the urgency of addressing climate risk as a strategic priority within the banking sector. However, climate-related disclosures, particularly those aligned with the CDP framework, mitigate these adverse effects. Additionally, derivative usage, especially for hedging purposes, emerges as an effective tool for safeguarding bank efficiency under climate stress. Our results also demonstrate that the interaction between ESG performance and disclosure practices amplifies the positive influence on efficiency, emphasizing the importance of integrating transparency with broader sustainability initiatives.

Despite these contributions, the study is subject to several limitations. First, CDP disclosure as a proxy for climate transparency may not fully capture the quality or comprehensiveness of climate-related reporting, as the CDP framework may vary in its implementation across different jurisdictions. While CDP provides a well-established measure of transparency, regulatory differences and disclosure standards may influence the comparability of these reports. Second, while CRISK serves as a valuable measure of systemic climate exposure, it does not account for bank-specific adaptation strategies or sectoral heterogeneity, which could affect how individual institutions manage climate risks. Climate risk exposure may be shaped by unique strategies or characteristics not captured in the current model. Third, while the truncated regression approach is suitable for efficiency scores bounded between zero and one, it assumes a parametric structure that may oversimplify the complexities inherent in the efficiency-generating process. Other statistical techniques could provide a more nuanced understanding of efficiency dynamics in the presence of climate-related factors. Lastly, despite efforts to control lag effects and institutional heterogeneity, potential endogeneity concerns remain, particularly in the relationship between climate risk and disclosure practices. These concerns could be addressed more rigorously through alternative methodological approaches.

Future research can extend this analysis in several key areas. First, exploring alternative disclosure measures—TCFD alignment or ISSB standards—may provide a more comprehensive understanding of the role of transparency in managing climate risk. These alternative frameworks may offer deeper insights into how the quality and comparability of climate disclosures affect financial performance. Second, employing dynamic panel methods or instrumental variable approaches could help address potential endogeneity concerns more rigorously, enhancing the robustness of the findings. Such techniques could offer more reliable inferences regarding the causal relationships between climate risk, disclosure practices, and efficiency. Third, disaggregating efficiency into cost, profit, and revenue dimensions may provide a finer-grained analysis of how climate-related variables impact different aspects of bank efficiency. This disaggregation could reveal important differences in how climate risks and risk management practices influence banks' operational outcomes. Finally, comparative studies across regulatory regimes or climate policy environments would offer valuable insights into the role of institutional and policy factors in shaping the effectiveness of climate risk management in the banking sector. Such studies could highlight how regulatory frameworks and policy environments interact with financial institutions' climate risk strategies.

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Table 1: Variable definition

Variables	Definition	Source
A. Bank-Level Data		
A1. Bank Efficiency		
Inputs		
Total Deposits	Total deposits from customers and other banks	
Total Cost	Total interest and non-interest expenditures	Authors' computation based on Bankscope data
Total Equity	Total book value of property, plant, and equipment (Total Equity=Total Assets−Total Liabilities)	The bank efficiency score is estimated using the DEA-Malmquist Approach.
Outputs		
Total Loans	Total loans to customers and other banks	
Non-Interest Income	Fee income and other non-interest income	
Other Earning Assets	Generate income beyond primary investments and loans, such as interest-bearing deposits, investment securities, and receivables.	
A2. Climate Risk Measures (Climate Stress Testing)		
Climate Stress Testing (Bank-Level Data)		
CRISK	The expected capital shortfall under climate stress is expressed in billions of USD.	Vlab website, accessed January 2024. https://vlab.stern.nyu.edu/climate The climate stress testing procedure involves three steps following Jung et al. (2022).
A3. Carbon Disclosure Measure		
CDP Disclosure	The dummy variable is set to one if the bank follows the Carbon Disclosure Project (CDP) to disclose its climate impacts (assessed through CDP disclosure) and zero otherwise.	Climate Disclosure Project (CDP) website, accessed March 2023. *https://www.cdp.net/en/companies/companies-scores*
A4. Responsible Banking Measures		
TCFD Member	The dummy variable is assigned a value of one if the bank is a member of the Task Force on Climate-Related Financial Disclosures (TCFD) and zero otherwise.	Task Force on Climate-related Financial Disclosures (TCFD) website, accessed March 2023. *https://www.fsb-cfd.org/supporters/*

Table 1: (Cont.)

Variables	Definition	Source
PRB Member	The dummy variable is coded as 1 for a bank that is a member of the Principles for Responsible Banking (PRB) and zero otherwise.	The United Nations Environment Programme Finance Initiative (UNEP FI) website, accessed March 2023. *https://www.unepfi.org/member*
A5. Climate Change, Commercial Risk and Opportunity		
CC-CRO Score	The CC-CRO score reflects the bank's resilience and adaptability in the context of climate change challenges. A higher score indicates greater resilience and adaptability, demonstrating the bank's preparedness to manage climate risks and capitalize on associated opportunities effectively.	Thomson Reuters Eikon (Refinitiv) Datastream
A6. ESG (Environmental, Social, and Governance)		
ESG Combined Score	The ESG score reflects how well a bank manages environmental, social, and governance factors relative to industry peers. This study calculates the ESG combined score by averaging the three individual pillar scores: Environmental (E), Social (S), and Governance (G). Scores typically range from 0 to 1, with higher scores indicating better ESG performance.	Thomson Reuters Eikon (Refinitiv) Datastream
A7. Financial Derivatives		
Gross Derivatives	The ratio of the gross notional amount of all derivatives (both hedging and trading) to total assets. This measures the overall exposure of a bank to derivatives.	Annual reports or Call reports
Hedging Derivatives	The ratio of the gross notional amount of hedging derivatives to total assets. This captures the extent to which derivatives are used for risk mitigation purposes.	
Trading Derivatives	The ratio of the gross notional amount of trading derivatives to total assets. This reflects the extent to which derivatives are used for speculative or profit-seeking activities.	
A8. Bank-level Controls		
Bank Size	The logarithm of total assets.	Authors' computation based on Bankscope data
Loans-to-Assets	Total loans to total assets.	
Deposits-to-Assets	Total deposits to total assets.	

Table 1: (Cont.)

Variables	Definition	Source
B. Country-Level Data		
B1. Climate-related Financial Policy		
Green Bond Issuances	Green bonds and sustainability-linked bonds are fixed-income securities designed specifically to support climate and environmental projects.	The International Monetary Fund (IMF), Climate Change Indicators Dashboard website, accessed December 2024. *https://climatedata.imf.org/datasets/8e2772e0b65f4e33a80183ce9583d062_0/explore*
B2. Country-level Controls		
Five Largest Banks	The share of the five largest banks as a proportion of total banking assets in a certain nation	World Bank Financial Development Database
GDP Growth	The real gross domestic product (GDP) growth rate	
Inflation Rate	Consumer price index (CPI)	
B3. Economic Shocks		
Dummy Crisis	The dummy variable is coded as 1 for the years 2008–2012 and 0 for the other periods.	Brunnermeier (2009), Reinhart and Rogoff (2009), Lane (2012)
Dummy COVID-19	The dummy variable is coded as 1 for the COVID-19 years 2020-2021 and 0 for the other periods.	(Goodell, 2020; IMF, 2020b)

Table 2: Descriptive statistics of the regression variables

Variables	Unit	Obs.	Mean	S.D.	Min	Max
Bank-Level Data						
Bank Efficiency						
Input						
Total Deposits	Billion USD	14,970	46.361	190.864	0.00004	4,289
Total Equity	Billion USD	14,970	0.744	5.989	0.02326	408.282
Total Cost	Billion USD	14,970	0.505	5.473	0.00001	392.561
Output						
Total Loans	Billion USD	14,970	46.939	145.817	0.00019	2,280
Non-Interest Income	Billion USD	14,970	1.207	5.103	0.00000	21.242
Other Earning Assets	Billion USD		44.405	151.524	0.00000	1,953
Climate Risk (Climate Stress Testing)						
CRISK	Billion USD	14,970	4.985	21.528	0.00368	89.491
Carbon Disclosure						
CDP Disclosure	Dummy	14,970	0.164	0.391	0.00000	1.000
Climate Change, Commercial Risk and Opportunity						
CC-CRO Score	Point	14,970	0.855	0.035	0.79118	0.920
Derivative Financial Instruments						
Gross Derivatives	Billion USD	14,970	16.100	178.000	0.00000	368.000
Hedging Derivatives	Billion USD	14,970	0.727	12.600	0.00000	14.100
Trading Derivatives	Billion USD	14,970	15.400	175.000	0.00000	349.000
ESG-Environmental, Social, and Governance						
ESG Combined Score	Point	14,970	0.435	0.224	0.01829	1.000
Control Variables						
Bank Size	Logarithm	14,970	20.514	0.837	8.67676	27.430
Loans-to-Assets	Point	14,970	0.511	0.282	0.00000	0.872
Deposits-to-Assets	Point	14,970	0.528	0.164	0.29012	0.769
Country-Level Data						
Climate-related Financial Policy						
Green Bond Issuances	Logarithm	14,970	0.332	1.164	0.00000	4.035
Country-level Controls						
Five Largest Banks	Point	14,970	0.600	0.202	0.00998	0.964
GDP Growth	Point	14,970	0.025	0.031	-0.26300	0.262
Inflation Ratio	Point	14,970	0.030	0.075	-0.04900	3.591
Economic Shocks						
Dummy Crisis	Dummy	14,970	0.248	0.432	0.00000	1.000
Dummy COVID-19	Dummy	14,970	0.111	0.314	0.00000	1.000

Note: This table reports descriptive statistics for the main variables, including the number of observations, mean, standard deviation, and range (minimum and maximum).

Table 3: Technical efficiency of the DEA approach

Country (DMU)	Technical Efficiency			Country (DMU)	Technical Efficiency		
	CRSTE	VRSTE	SCALE		CRSTE	VRSTE	SCALE
1. Argentina	0.8044	0.8427	0.9536	36. Malta	0.9563	0.9606	0.9955
2. Australia	0.9344	0.9528	0.9803	37. Mauritius	0.9514	0.9766	0.9743
3. Austria	0.9243	0.9555	0.9674	38. Mexico	0.6729	0.6845	0.9839
4. Bahrain	0.8626	0.9012	0.9561	39. Morocco	0.8197	0.8274	0.9847
5. Bangladesh	0.8239	0.8854	0.9310	40. Netherlands	0.8100	0.8701	0.9192
6. Belgium	0.9003	0.9305	0.9670	41. New Zealand	0.8145	0.8752	0.9238
7. Bermuda	0.8793	0.9365	0.9390	42. Nigeria	0.9328	0.9733	0.9578
8. Brazil	0.9214	0.9520	0.9668	43. Norway	0.8254	0.9203	0.8970
9. Canada	0.9174	0.9470	0.9689	44. Oman	0.9145	0.9220	0.9914
10. Chile	0.9259	0.9451	0.9798	45. Pakistan	0.9637	0.9758	0.9874
11. China	0.9212	0.9319	0.9879	46. Peru	0.9627	0.9683	0.9943
12. Colombia	0.8917	0.9362	0.9521	47. Philippines	0.8806	0.8908	0.9872
13. Croatia	0.8440	0.8551	0.9864	48. Poland	0.9629	0.9687	0.9939
14. Cyprus	0.9444	0.9709	0.9724	49. Portugal	0.6165	0.6632	0.9311
15. Czech Republic	0.9557	0.9823	0.9728	50. Puerto Rico	0.3712	0.3848	0.9655
16. Denmark	0.8896	0.9167	0.9702	51. Qatar	0.4434	0.4813	0.9313
17. Egypt	0.8690	0.9291	0.9320	52. Russia	0.6290	0.6953	0.9198
18. Finland	0.9335	0.9628	0.9696	53. Saudi Arabia	0.7923	0.8196	0.9645
19. France	0.8676	0.9141	0.9452	54. Singapore	0.9301	0.9563	0.9728
20. Germany	0.8675	0.9216	0.9390	55. South Africa	0.9076	0.9564	0.9465
21. Greece	0.9251	0.9344	0.9901	56. South Korea	0.9294	0.9489	0.9776
22. Hong Kong	0.9390	0.9593	0.9769	57. Spain	0.9387	0.9505	0.9873
23. Iceland	0.8492	0.9003	0.9432	58. Sri Lanka	0.9622	0.9774	0.9843
24. India	0.8699	0.9076	0.9583	59. Sweden	0.9053	0.9443	0.9597
25. Indonesia	0.8742	0.8942	0.9759	60. Switzerland	0.9000	0.9405	0.9549
26. Ireland	0.9518	0.9857	0.9649	61. Taiwan	0.8716	0.8965	0.9704
27. Israel	0.8950	0.9180	0.9749	62. Thailand	0.9368	0.9580	0.9775
28. Italy	0.9308	0.9546	0.9740	63. Tunisia	0.9266	0.9785	0.9472
29. Japan	0.9371	0.9603	0.9755	64. Turkey	0.8978	0.9300	0.9642
30. Jordan	0.8689	0.9656	0.8999	65. Ukraine	0.9379	0.9657	0.9715
31. Kazakhstan	0.9743	0.9896	0.9845	66. U.A.E	0.9322	0.9580	0.9722
32. Kenya	0.9207	0.9825	0.9362	67. U.K	0.8794	0.9336	0.9402
33. Kuwait	0.9357	0.9553	0.9786	68. U.S	0.9051	0.9461	0.9522
34. Lebanon	0.9528	0.9628	0.9894	69. Vietnam	0.9308	0.9507	0.9784
35. Malaysia	0.9550	0.9620	0.9926				

Note: This table presents the technical efficiency scores derived from the DEA analysis across countries. The scores are computed based on three different assumptions: Constant Returns to Scale (CRSTE) model, Variable Returns to Scale (VRSTE) model, and Scale Efficiency (SCALE) model.

Table 4: The fluctuation of the Malmquist Total Productivity index

Country	Malmquist Index				Country	Malmquist Index			
(DMU)	TFPCH	TECH	TECCH	SECH	(DMU)	TFPCH	TECH	TECCH	SECH
1. Argentina	1.0041	1.0458	0.9735	1.0016	36. Malta	1.0222	1.0871	0.9656	1.0010
2. Australia	1.0487	1.0780	0.9843	1.0001	37. Mauritius	1.0002	1.0907	0.9580	1.0015
3. Austria	1.0512	1.0850	0.9795	1.0028	38. Mexico	1.0402	1.0772	0.9738	1.0017
4. Bahrain	1.0298	1.0567	0.9877	1.0025	39. Morocco	1.0138	1.0599	0.9727	1.0021
5. Bangladesh	1.0192	1.0592	0.9797	1.0034	40. Netherlands	1.0099	1.0441	0.9779	1.0011
6. Belgium	1.0403	1.0705	0.9848	1.0022	41. New Zealand	1.0111	1.0384	0.9971	1.0006
7. Bermuda	1.0078	1.0345	0.9837	0.9981	42. Nigeria	1.0577	1.0820	0.9722	1.0200
8. Brazil	1.0506	1.0626	0.9761	0.9999	43. Norway	1.0185	1.0495	0.9828	0.9991
9. Canada	1.0866	1.0994	0.9902	1.0000	44. Oman	1.0358	1.0697	0.9824	1.0027
10. Chile	1.0310	1.0645	0.9808	1.0019	45. Pakistan	1.0354	1.0842	0.9695	1.0029
11. China	1.0307	1.0442	0.9875	1.0014	46. Peru	1.0199	1.0673	0.9623	1.0040
12. Colombia	1.0487	1.0860	0.9667	1.0028	47. Philippines	1.0370	1.0768	0.9760	1.0040
13. Croatia	1.0495	1.0656	0.9854	1.0049	48. Poland	1.0025	1.0368	0.9725	1.0041
14. Cyprus	1.0447	1.0559	0.9925	0.9993	49. Portugal	1.0367	1.0518	0.9875	1.0013
15. Czech Republic	1.0612	1.0882	0.9671	1.0041	50. Puerto Rico	0.9995	1.0429	0.9676	1.0000
16. Denmark	1.0258	1.0610	0.9822	1.0007	51. Qatar	1.0025	1.0312	0.9798	1.0054
17. Egypt	1.1119	1.1369	0.9856	1.0025	52. Russia	1.1236	1.1289	0.9923	1.0070
18. Finland	1.0157	1.0354	0.9899	0.9989	53. Saudi Arabia	1.0482	1.0621	0.9784	1.0037
19. France	1.0070	1.0387	0.9839	0.9993	54. Singapore	1.0461	1.0799	0.9752	0.9997
20. Germany	1.0264	1.0535	0.9816	1.0064	55. South Africa	1.0470	1.0724	0.9773	1.0043
21. Greece	1.0151	1.0321	0.9911	0.9958	56. South Korea	1.0109	1.0200	0.9907	1.0060
22. Hong Kong	1.0705	1.0781	0.9942	1.0041	57. Spain	1.0471	1.0800	0.9787	0.9929
23. Iceland	0.9972	0.9968	1.0012	0.9993	58. Sri Lanka	1.0371	1.1007	0.9751	1.0043
24. India	1.0310	1.0747	0.9792	1.0025	59. Sweden	1.0267	1.0584	0.9815	1.0003
25. Indonesia	1.0427	1.0788	0.9734	1.0052	60. Switzerland	1.0208	1.0633	0.9786	0.9993
26. Ireland	1.0225	1.0641	0.9827	0.9979	61. Taiwan	1.0355	1.0753	0.9748	1.0000
27. Israel	1.0072	1.0506	0.9688	0.9958	62. Thailand	1.0338	1.0706	0.9762	1.0022
28. Italy	1.0508	1.0752	0.9842	0.9991	63. Tunisia	1.0339	1.1005	0.9757	1.0010
29. Japan	1.0356	1.0506	0.9886	0.9976	64. Turkey	1.0360	1.0682	0.9769	1.0032
30. Jordan	1.0200	1.0700	0.9703	1.0023	65. Ukraine	1.0079	1.0408	0.9862	0.9934
31. Kazakhstan	1.0289	1.0717	0.9750	0.9996	66. U.A.E	1.0532	1.0573	0.9773	1.0052
32. Kenya	1.0296	1.0950	0.9642	1.0068	67. U.K	1.0471	1.0511	0.9870	1.0053
33. Kuwait	1.0628	1.0941	0.9740	1.0035	68. U.S	1.0361	1.0553	0.9872	1.0034
34. Lebanon	1.0153	1.0437	0.9823	0.9965	69. Vietnam	1.0283	1.0459	0.9827	1.0034
35. Malaysia	1.0422	1.0807	0.9719	1.0030					

Note: This table reports the Malmquist Total Factor Productivity Index (TFPCH) and its components—technological change (TECH), technical efficiency change (TECCH), and scale efficiency change (SECH)—for banks across countries from 2001 to 2021. TFPCH captures overall productivity shifts, combining both efficiency improvements and technological progress.

Table 5: Technical efficiency and the changes of Malmquist Total Productivity index by year

Panel A: Technical Efficiency				Panel B: Malmquist Index				
Year	CRSTE	VRSTE	SCALE	Year Period	TFPCH	TECH	TECCH	SECH
2001	0.8687	0.9149	0.9446					
2002	0.8689+	0.9135-	0.9476+	2001-2002	1.0510	1.0440	1.0029	1.0017
2003	0.8681-	0.9147+	0.9468-	2002-2003	1.0459	1.0464	0.9945	0.9978
2004	0.8700+	0.9140-	0.9497+	2003-2004	1.0560	0.9951	1.0659	1.0010
2005	0.8850+	0.9238+	0.9559+	2004-2005	1.2134	1.3122	0.9003	1.0088
2006	0.8945+	0.9300+	0.9591+	2005-2006	1.1162	1.0722	1.0398	1.0053
2007	0.8953+	0.9299-	0.9600+	2006-2007	1.0674	1.0651	0.9981	1.0056
2008	0.8967+	0.9316+	0.9601+	2007-2008	1.0447	1.1055	0.9398	0.9998
2009	0.8978+	0.9334+	0.9595-	2008-2009	1.0756	1.0326	1.0568	1.0028
2010	0.8963-	0.9329-	0.9579-	2009-2010	1.0411	1.4497	0.7585	1.0007
2011	0.9065+	0.9428+	0.9601+	2010-2011	1.0506	1.0444	1.0005	1.0027
2012	0.9056-	0.9400-	0.9617+	2011-2012	1.0107	0.9691	1.0382	1.0052
2013	0.9087+	0.9408+	0.9626+	2012-2013	1.0142	1.0205	0.9913	1.0014
2014	0.9091+	0.9430+	0.9612-	2013-2014	1.0152	1.0245	0.9883	1.0023
2015	0.9166+	0.9469+	0.9650+	2014-2015	1.0150	1.0510	0.9628	1.0024
2016	0.9111-	0.9430-	0.9629-	2015-2016	1.0070	1.0123	0.9907	1.0028
2017	0.9108-	0.9431+	0.9626-	2016-2017	1.0122	1.0180	0.9912	1.0020
2018	0.9152+	0.9445+	0.9655+	2017-2018	1.0064	0.9888	1.0166	1.0025
2019	0.9121-	0.9436-	0.9639-	2018-2019	1.0192	1.0225	0.9923	1.0014
2020	0.9037-	0.9378-	0.9618-	2019-2020	0.9591	0.9728	0.9854	1.0024
2021	0.8990-	0.9357-	0.9595-	2020-2021	0.9822	1.0127	0.9815	1.0000
Obs.	14,970	14,970	14,970	Obs.	14,970	14,970	14,970	14,970
Mean	0.8998	0.9351	0.9595	Mean	1.0360	1.0601	0.9839	1.0025
S.D.	0.1191	0.0998	0.0736	S.D.	0.3055	0.3137	0.0992	0.0492
Median	0.9336	0.9675	0.9854	Median	1.0004	1.0023	0.9973	1.0004
Minimum	0.3529	0.3758	0.6610	Minimum	0.4031	0.4572	0.5177	0.8692
Maximum	1.0000	1.0000	1.0000	Maximum	4.3008	3.6681	2.0466	2.1714

Note: This table presents annual trends in bank efficiency from 2001 to 2021. Panel A reports technical efficiency scores—CRSTE, VRSTE, and SCALE—capturing relatively stable efficiency with marginal year-to-year variation. Panel B details the components of the Malmquist productivity index—TFPCH, TECH, TECCH, and SECH—capturing shifts in productivity driven by efficiency gains and technological change.

Table 6: Baseline models

Variable	CRSTE	CRSTE	CRSTE	VRSTE	VRSTE	VRSTE
	(1)	(2)	(3)	(4)	(5)	(6)
L.Dependent	5.303***	6.889***	5.372***	1.166***	1.170***	1.170***
	(0.0925)	(0.1935)	(0.0947)	(0.0089)	(0.0090)	(0.0090)
CRISK	-0.00135**	-0.00150**	-0.00116*	-0.00153**	-0.00156**	-0.00168**
	(0.0006)	(0.0006)	(0.0006)	(0.0007)	(0.0007)	(0.0007)
CDP Disclosure	0.0219***	0.0275***	0.0189***	0.0143***	0.0139***	0.0139***
	(0.0023)	(0.0026)	(0.0023)	(0.0029)	(0.0029)	(0.0029)
Gross Derivatives	0.0156***			0.00710***		
	(0.0007)			(0.0014)		
Hedging Derivatives		0.0226***			0.0263***	
		(0.0048)			(0.0078)	
Trading Derivatives			0.0148***			0.00672***
			(0.0007)			(0.0015)
ESG Combined Score	0.0187***	0.0208***	0.0030	0.0023	0.0048	0.0050
	(0.0026)	(0.0029)	(0.0025)	(0.0032)	(0.0033)	(0.0033)
CC-CRO Score	-0.0012	-0.0892***	-0.172***	-0.0586	-0.0563	-0.0574
	(0.0309)	(0.0304)	(0.0291)	(0.0373)	(0.0374)	(0.0375)
Green Bond Issuances	0.00003	0.00148	0.00136	0.0042***	0.00482***	0.00479***
	(0.0010)	(0.0011)	(0.0010)	(0.0013)	(0.0013)	(0.0013)
Bank Size	-0.0008	0.0013	0.0045**	0.0107***	0.0104***	0.0107***
	(0.0021)	(0.0021)	(0.0020)	(0.0026)	(0.0026)	(0.0026)
Five Largest Banks	-0.0137**	-0.0003	0.0105**	-0.0017	-0.0005	-0.0014
	(0.0054)	(0.0053)	(0.0050)	(0.0062)	(0.0062)	(0.0062)
Loans-to-Assets	0.0289***	0.120***	0.219***	0.0603***	0.0595***	0.0596***
	(0.0040)	(0.0067)	(0.0054)	(0.0052)	(0.0052)	(0.0052)
Deposits-to-Assets	0.0125	0.0913***	0.173***	0.0200*	0.0226**	0.0220*
	(0.0090)	(0.0099)	(0.0090)	(0.0112)	(0.0113)	(0.0113)
GDP Growth	0.100***	0.100***	0.165***	-0.164***	-0.184***	-0.179***
	(0.0380)	(0.0365)	(0.0355)	(0.0448)	(0.0451)	(0.0451)
Inflation Ratio	-0.0079	-0.0521***	-0.0990***	-0.0406***	-0.0471***	-0.0487***
	(0.0136)	(0.0143)	(0.0137)	(0.0136)	(0.0139)	(0.0139)
Dummy Crisis	0.0012	0.0010	0.0017	0.0044	0.0042	0.0042
	(0.0025)	(0.0025)	(0.0025)	(0.0031)	(0.0031)	(0.0031)
Dummy COVID-19	-0.0237***	-0.0253***	-0.0229***	-0.0327***	-0.0334***	-0.0329***
	(0.0044)	(0.0045)	(0.0043)	(0.0055)	(0.0056)	(0.0056)
Constant	-6.492***	-8.811***	-6.771***	-0.281***	-0.284***	-0.289***
	(0.1422)	(0.2810)	(0.1490)	(0.0572)	(0.0574)	(0.0575)
Sigma	0.0849***	0.0876***	0.0853***	0.0874***	0.0876***	0.0877***
	(0.0008)	(0.0009)	(0.0008)	(0.0010)	(0.0010)	(0.0010)
Fixed Effects	Yes	Yes	Yes	Yes	Yes	Yes
No of Banks	1,175	1,175	1,175	1,175	1,175	1,175
Year	2001-2021	2001-2021	2001-2021	2001-2021	2001-2021	2001-2021
Obs.	17,159	17,159	17,159	17,159	17,159	17,159
Truncated Obs.	14,970	14,970	14,970	14,198	14,198	14,198
Wald -test	12,562	11,660	12,374	17,675	17,578	17,536
Prob > χ^2	0.000	0.000	0.000	0.000	0.000	0.000
Log-Likelihood	25,735	25,478	25,729	26,767	26,765	26,770
AIC	-51,429	-50,915	-51,416	-53,492	-53,485	-53,497
BIC	-51,269	-50,755	-51,256	-53,334	-53,319	-53,330
Highest VIF	2.730	2.730	2.730	2.730	2.730	2.730
Mean of VIF	1.300	1.300	1.300	1.300	1.290	1.300

Note: This table presents the baseline truncated regression models assessing the relationship between climate risk and bank efficiency. The dependent variable is bank efficiency (CRSTE and VRSTE), and the key explanatory variables include climate risk (CRISK), CDP disclosure, and financial derivative instruments. The models control for unobserved heterogeneity using bank-, country-, and time-fixed effects. Standard errors, clustered at the bank, country, and year levels, are shown in parentheses. Statistical significance is denoted by ***, **, and * for the 1%, 5%, and 10% levels, respectively. Variable definitions are provided in Table 1.

Table 7: Baseline models—The interaction effects

Variable	CRSTE (1)	CRSTE (2)	CRSTE (3)	VRSTE (4)	VRSTE (5)	VRSTE (6)
L.Dependent	5.379***	4.550***	5.360***	1.158***	1.160***	1.160***
	(0.0945)	(0.0827)	(0.0943)	(0.0089)	(0.0090)	(0.0090)
CRISK	-0.0866***	-0.0651***	-0.0869***	-0.0025***	-0.0026***	-0.0027***
	(0.0096)	(0.0095)	(0.0096)	(0.0007)	(0.0007)	(0.0007)
CDP Disclosure	0.0115***	0.0109***	0.0114***	0.00619	0.00700*	0.00711*
	(0.0032)	(0.0033)	(0.0032)	(0.0042)	(0.0042)	(0.0042)
Gross Derivatives	0.0133***			0.0035***		
	(0.0007)			(0.0013)		
Hedging Derivatives		0.0283***			0.0129*	
		(0.0050)			(0.0066)	
Trading Derivatives			0.0137***			0.0033**
			(0.0007)			(0.0013)
ESG Combined Score	-0.0216***	-0.0149***	-0.0212***	-0.00528	-0.00271	-0.00246
	(0.0035)	(0.0035)	(0.0035)	(0.0041)	(0.0043)	(0.0043)
CRISK×CDP_Disclosure	0.00128***	0.000972***	0.00128***	0.0000805	0.0000782	0.0000838
	(0.0001)	(0.0001)	(0.0001)	(0.0001)	(0.0001)	(0.0001)
CRISK×Derivative_Users	0.00315***	0.00604***	0.00345***	0.00528***	0.00544***	0.00527***
	(0.0004)	(0.0004)	(0.0004)	(0.0006)	(0.0006)	(0.0006)
ESG×CDP_Disclosure	0.000578***	0.000495***	0.000576***	0.000180***	0.000157**	0.000154**
	(0.0001)	(0.0001)	(0.0001)	(0.0001)	(0.0001)	(0.0001)
CC-CRO Score	-0.172***	-0.143***	-0.173***	-0.0446	-0.0435	-0.0444
	(0.0288)	(0.0290)	(0.0288)	(0.0375)	(0.0376)	(0.0376)
Green Bond Issuances	0.000258	0.00025	0.0002	0.00296**	0.00332**	0.00334**
	(0.0010)	(0.0010)	(0.0010)	(0.0013)	(0.0013)	(0.0013)
Bank Size	0.00585***	0.00549***	0.00584***	0.00949***	0.00930***	0.00949***
	(0.0020)	(0.0020)	(0.0020)	(0.0026)	(0.0026)	(0.0026)
Five Largest Banks	0.0171***	0.0238***	0.0166***	-0.000145	0.000625	0.0000968
	(0.0052)	(0.0052)	(0.0052)	(0.0062)	(0.0062)	(0.0062)
Loans-to-Assets	0.214***	0.178***	0.213***	0.0497***	0.0491***	0.0494***
	(0.0054)	(0.0051)	(0.0054)	(0.0052)	(0.0052)	(0.0052)
Deposits-to-Assets	0.169***	0.140***	0.168***	0.0207*	0.0221*	0.0219*
	(0.0090)	(0.0089)	(0.0090)	(0.0113)	(0.0113)	(0.0113)
GDP Growth	0.201***	0.173***	0.200***	-0.177***	-0.189***	-0.186***
	(0.0351)	(0.0355)	(0.0352)	(0.0452)	(0.0454)	(0.0454)
Inflation Ratio	-0.0985***	-0.0810***	-0.0988***	-0.0434***	-0.0480***	-0.0487***
	(0.0140)	(0.0141)	(0.0140)	(0.0138)	(0.0140)	(0.0140)
Dummy Crisis	0.00184	0.00152	0.00194	0.00524*	0.00507	0.00506
	(0.0024)	(0.0025)	(0.0024)	(0.0031)	(0.0031)	(0.0031)
Dummy COVID-19	-0.0227***	-0.0252***	-0.0225***	-0.0330***	-0.0335***	-0.0332***
	(0.0043)	(0.0043)	(0.0043)	(0.0056)	(0.0056)	(0.0056)
Constant	-6.245***	-5.158***	-6.208***	-0.260***	-0.262***	-0.265***
	(0.1549)	(0.1429)	(0.1546)	(0.0576)	(0.0577)	(0.0577)
Sigma	0.0844***	0.0853***	0.0845***	0.0877***	0.0879***	0.0879***
	(0.0008)	(0.0008)	(0.0008)	(0.0010)	(0.0010)	(0.0010)
Fixed Effects	Yes	Yes	Yes	Yes	Yes	Yes
No of Banks	1,175	1,175	1,175	1,175	1,175	1,175
Year	2001-2021	2001-2021	2001-2021	2001-2021	2001-2021	2001-2021
Obs.	17,159	17,159	17,159	17,159	17,159	17,159
Truncated Obs.	14,970	14,970	14,970	14,198	14,198	14,198
Wald -test	12,544	12,599	12,523	17,646	17,568	17,526
Prob > χ^2	0.000	0.000	0.000	0.000	0.000	0.000
Log-Likelihood	25,858	25,471	25,844	26,771	26,767	26,773
AIC	-51,671	-50,897	-51,641	-53,497	-53,487	-53,498
BIC	-51,495	-50,722	-51,466	-53,323	-53,305	-53,317
Highest VIF	4.350	4.340	4.350	4.320	4.320	4.320
Mean of VIF	1.650	1.650	1.650	1.590	1.590	1.590

Note: The models control for unobserved heterogeneity using bank-, country-, and time-fixed effects. Standard errors are reported in parentheses and calculated with standard errors clustering by bank, country, and year. The asterisks (***, **, *) represent the statistical significance levels of 1%, 5%, and 10%, respectively. Variable definitions are in Table 1.

Table 8: Endogeneity issue—Instrument variables

Variable	First-Stage DumCDP_Disclosure	Second-Stage (2LSL) CRSTE
TCFD Member	0.0315***	
	(0.0104)	
PRB Member	0.1141***	
	(0.0133)	
CDP Disclosure		0.0578***
		(0.0134)
L.Dependent	2.7112***	2.1959***
	(0.2729)	(0.1753)
CRISK	0.006***	-0.0012***
	(0.0015)	(0.0003)
Gross Derivatives	0.0037**	0.0043***
	(0.0017)	(0.0006)
ESG Combined Score	0.0585***	0.0104***
	(0.0066)	(0.0020)
CC-CRO Score	0.2059**	-0.0230
	(0.0923)	(0.0181)
Green Bond Issuances	0.0030	0.0003
	(0.0033)	(0.0005)
Bank Size	0.0362***	-0.0031***
	(0.0061)	(0.0011)
Five Largest Banks	0.0200	-0.0069**
	(0.0169)	(0.0033)
Loans-to-Assets	-0.0149	0.0173***
	(0.0101)	(0.0026)
Deposits-to-Assets	-0.00001	0.0009
	(0.0269)	(0.0047)
GDP Growth	0.2051*	0.0838***
	(0.1233)	(0.0277)
Inflation Ratio	0.0321	-0.0001
	(0.0462)	(0.0049)
Dummy Crisis	-0.0066	0.0012
	(0.0072)	(0.0014)
Dummy COVID-19	-0.0097	-0.0070***
	(0.0134)	(0.0024)
Constant	3.3763***	-1.9375***
	(0.4335)	(0.2708)
Fixed Effects	Yes	Yes
No of Banks	1,175	1,175
Year	2001-2021	2001-2021
Obs.	17,159	17,159
Truncated Obs.	14,970	14,970
F(2, 14948)	53.990	
F(19, 14949)		793.410
Prob > F	0.000	0.000
R^2		0.673

Note: This table presents the results of addressing potential endogeneity concerns using instrumental variables (IV). The table is organized into two stages: the first-stage model and the second-stage two-stage least squares (2SLS) regression. In the first stage, the instrument variable used to predict the endogenous regressor—the dummy variable for carbon disclosure—DumCDP_Disclosure—mitigates endogeneity issues. The second stage estimates the impact of the predicted variable on bank efficiency—CRSTE—while controlling for potential endogeneity. The models control for unobserved heterogeneity using bank-, country-, and time-fixed effects. Standard errors are reported in parentheses and clustered at the bank, country, and year levels to account for potential intra-group correlations. Statistical significance is denoted by ***, **, and * for the 1%, 5%, and 10% levels, respectively. Detailed variable definitions are provided in Table 1.

Table 9: Endogeneity issue—Model diagnostic test

Model Diagnostic Test	Test Statistic	P-value	Interpretation
Underidentification Test (Kleibergen-Paap LM Test)	$\chi^2(2) = 106.03$	0.0000	The model is identified, and the instruments explain variation in the endogenous variable.
Weak Identification Test (Cragg-Donald F Test)	70.62	-	It exceeds the Stock-Yogo critical value (19.93), indicating that the instruments are not weak.
Kleibergen-Paap Wald rk F statistic	53.99	-	Confirms strong instruments under heteroskedasticity-robust conditions.
Stock-Yogo Weak ID Test Critical Values	10% max IV size = 19.93	-	It ensures robustness against weak instruments.
Overidentification Test (Hansen J Test)	$\chi^2(1) = 0.061$	0.8044	It can not reject the null hypothesis; the instruments are valid.
Endogeneity Test (Durbin-Wu-Hausman Test)	$\chi^2(1) = 19.17$	0.0000	It rejects the null hypothesis, confirming that the endogenous regressor (CDP disclosure) is endogenous and requires instrumentation.
Weak-Instrument Robust Inference (Anderson-Rubin Test)	F(2,14948) = 11.05	0.0000	It is significant and supports the joint validity of instruments.
Anderson-Rubin Wald χ^2 Test	$\chi^2(2) = 22.13$	0.0000	It suggests the instruments explain endogenous regressors well.
Stock-Wright LM S Test	$\chi^2(2) = 26.02$	0.0000	It supports the validity of instruments under weak-identification-robust conditions.
Overall Model Fit (F-statistic)	F(2, 14,948)=53.99	0.0000	The model is highly significant.
R^2(Centered)	0.673	-	Moderate explanatory power of the model.
Root Mean Squared Error (RMSE)	0.065	-	It indicates the average prediction error.
Number of observations	14,970		
Number of regressors	20		
Number of endogenous regressors	1		
Number of instruments	21		
Number of excluded instruments	2		

Note: This table presents the results of various diagnostic tests to address endogeneity concerns and evaluate the validity of the model's instruments.

Table 10: Robustness test—GMM Model

Variable	CRSTE	CRSTE	CRSTE	VRSTE	VRSTE	VRSTE	CRSTE	CRSTE	CRSTE	VRSTE	VRSTE	VRSTE
	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)	(9)	(10)	(11)	(12)
L.Dependent	2.062***	2.040***	2.062***	0.886***	0.886***	0.886***	1.360***	1.847***	1.363***	0.849***	0.854***	0.849***
	(0.0417)	(0.0462)	(0.0418)	(0.0039)	(0.0040)	(0.0039)	(0.2878)	(0.1365)	(0.2724)	(0.0154)	(0.0130)	(0.0149)
L.CRISK	-0.00084***	-0.00066**	-0.00085***	-0.00078***	-0.00078***	-0.00077***	-0.0022***	-0.0026***	-0.0022***	-0.0043***	-0.0038***	-0.0042***
	(0.00026)	(0.00029)	(0.00026)	(0.0003)	(0.0003)	(0.0003)	(0.0007)	(0.0010)	(0.0007)	(0.0014)	(0.0012)	(0.0014)
L.CDP Disclosure	0.00502***	0.00509***	0.00501***	0.000925	0.00106	0.00105	0.00683**	0.00533***	0.00685**	-0.00171	-0.00141	-0.00168
	(0.0011)	(0.0013)	(0.0011)	(0.0011)	(0.0011)	(0.0011)	(0.0032)	(0.0018)	(0.0031)	(0.0019)	(0.0018)	(0.0019)
L.Gross Derivatives	0.00415***			0.00008			-0.0039			0.00377**		
	(0.0002)			(0.0002)			(0.0030)			(0.0015)		
L.Hedging Derivatives		0.0823***			0.00257			0.0209			0.0121**	
		(0.0052)			(0.0039)			(0.0301)			(0.0050)	
L.Trading Derivatives			0.00435***			0.0000785			-0.0041			0.00355**
			(0.0002)			(0.0002)			(0.0030)			(0.0014)
L.ESG Combined Score	0.00505***	0.00221	0.00520***	-0.00124	-0.00176	-0.00167	-0.00374	-0.00829***	-0.00391	-0.00364*	-0.00317*	-0.00376*
	(0.0013)	(0.0015)	(0.0013)	(0.0012)	(0.0013)	(0.0013)	(0.0028)	(0.0025)	(0.0028)	(0.0020)	(0.0019)	(0.0020)
L.CRISK×CDP_Disclosure							0.00113**	0.000215***	0.00112**	0.0000118	0.0000173	0.0000122
							(0.0005)	(0.0000)	(0.0004)	(0.0000)	(0.0000)	(0.0000)
L.CRISK×Derivative_Users							0.00015***	0.00018***	0.00015***	0.000057*	0.000047	0.000057*
							(0.0000)	(0.0000)	(0.0000)	(0.0000)	(0.0000)	(0.0000)
L.ESG×CDP_Disclosure							0.0235***	0.00832*	0.0234***	0.0129**	0.0109***	0.0126***
							(0.0084)	(0.0045)	(0.0079)	(0.0051)	(0.0041)	(0.0049)
Control Variables	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes
Fixed Effects	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes
No of Banks	1,175	1,175	1,175	1,175	1,175	1,175	1,175	1,175	1,175	1,175	1,175	1,175
Year	2001-2021	2001-2021	2001-2021	2001-2021	2001-2021	2001-2021	2001-2021	2001-2021	2001-2021	2001-2021	2001-2021	2001-2021
Obs.	17,159	17,159	17,159	17,159	17,159	17,159	17,159	17,159	17,159	17,159	17,159	17,159
Truncated Obs.	14,970	14,970	14,970	14,970	14,970	14,970	14,970	14,970	14,970	14,970	14,970	14,970
R^2	0.702	0.697	0.702	0.788	0.788	0.788	0.705	0.699	0.704	0.788	0.788	0.788
F-statistic	1,857	1,808	1,854	2,773	2,635	2,635	1,620	1,655	1,618	2,395	2,395	2,395
Prob > F	0.000	0.000	0.000	0.000	0.000	0.000	0.000	0.000	0.000	0.000	0.000	0.000
Root MSE	0.062	0.063	0.062	0.058	0.058	0.058	0.062	0.062	0.062	0.058	0.058	0.058

Note: This table presents the results of the robustness test using the Generalized Method of Moments (GMM) model. The table includes estimates for the relationship between climate risk, carbon disclosure, and bank efficiency. The GMM model is employed to address potential endogeneity and other specification concerns. Control variables include CC-CRO score, bank size, loans-to-assets, deposits-to-assets, green bond issuances, five largest banks, GDP growth, inflation ratio, dummy crisis, and dummy COVID-19. The models control for unobserved heterogeneity using bank-, country-, and time-fixed effects. Standard errors are reported in parentheses and clustered at the bank, country, and year levels to account for potential intra-group correlations. Statistical significance is denoted by ***, **, and * for the 1%, 5%, and 10% levels, respectively. Detailed variable definitions are provided in Table 1.

Table 11: Robustness test—Difference-in-Difference (DiD) regression

Variable	ATET: Gross Derivatives (Control = 0; Treatment = 1)				ATET: Hedging Derivatives (Control = 0; Treatment = 1)				ATET: Trading Derivatives (Control = 0; Treatment = 1)			
	CRSTE	CRSTE	VRSTE	VRSTE	CRSTE	CRSTE	VRSTE	VRSTE	CRSTE	CRSTE	VRSTE	VRSTE
	(1)	(7)	(4)	(10)	(2)	(8)	(5)	(11)	(3)	(9)	(6)	(12)
ATET												
Gross Derivatives	0.00707***	0.00804***	0.0023	0.0024								
	(0.0027)	(0.0026)	(0.0029)	(0.0029)								
Hedging Derivatives					0.00620**	0.00662**	0.00001	0.00014				
					(0.0031)	(0.0030)	(0.0030)	(0.0030)				
Trading Derivatives									0.00908**	0.0116***	0.00608*	0.00618*
									(0.0037)	(0.0036)	(0.0036)	(0.0036)
Controls												
L.Dependent	0.373***	1.160***	0.459***	0.466***	0.374***	1.157***	0.458***	0.466***	0.373***	1.166***	0.458***	0.466***
	(0.0366)	(0.1818)	(0.0636)	(0.0531)	(0.0365)	(0.1828)	(0.0636)	(0.0532)	(0.0366)	(0.1818)	(0.0635)	(0.0532)
CRISK	-0.0036***	-0.0147***	-0.0019***	-0.00019	-0.0036***	-0.0146***	-0.0019***	0.00017	-0.0036***	-0.0147***	-0.0019***	-0.00007
	(0.0006)	(0.0042)	(0.0005)	(0.0032)	(0.0006)	(0.0043)	(0.0005)	(0.0031)	(0.0006)	(0.0043)	(0.0005)	(0.0032)
CDP Disclosure	0.0014	0.0021	0.0011	0.0001	0.0014	0.0020	0.0011	0.0005	0.0015	0.0020	0.0011	0.0005
	(0.0014)	(0.0015)	(0.0012)	(0.0013)	(0.0014)	(0.0015)	(0.0012)	(0.0014)	(0.0014)	(0.0015)	(0.0012)	(0.0014)
ESG Combined Score	0.00713*	-0.00721*	0.0032	0.0028	0.00713*	-0.00703*	0.0033	0.0035	0.00712*	-0.00756*	0.0031	0.0032
	(0.0038)	(0.0041)	(0.0030)	(0.0032)	(0.0038)	(0.0041)	(0.0030)	(0.0033)	(0.0038)	(0.0041)	(0.0030)	(0.0033)
CRISK×CDP_Disclosure		0.00017***		-0.00002		0.00017***		-0.00003		0.00017***		-0.00002
		(0.0001)		(0.0000)		(0.0001)		(0.0000)		(0.0001)		(0.0000)
ESG×CDP_Disclosure		0.00014***		0.00002		0.00015***		0.00001		0.000149***		0.00001
		(0.0000)		(0.0000)		(0.0000)		(0.0000)		(0.0000)		(0.0000)
CC-CRO Score	0.0428	-0.0152	0.0245	0.0145	0.0424	-0.0152	0.0248	0.0152	0.0435	-0.0154	0.0248	0.0154
	(0.0286)	(0.0256)	(0.0302)	(0.0311)	(0.0284)	(0.0256)	(0.0301)	(0.0310)	(0.0286)	(0.0256)	(0.0302)	(0.0309)
Green Bond Issuances	-0.0015**	-0.0012*	-0.0009	-0.0008	-0.0014**	-0.0011	-0.0008	-0.0006	-0.00132*	-0.0010	-0.0009*	-0.0007
	(0.0007)	(0.0007)	(0.0005)	(0.0006)	(0.0007)	(0.0007)	(0.0005)	(0.0006)	(0.0007)	(0.0007)	(0.0005)	(0.0006)
Bank Size	0.0093***	0.0095***	0.0071***	0.0073***	0.0094***	0.0097***	0.0072***	0.0074***	0.0093***	0.0094***	0.0069***	0.0070***
	(0.0016)	(0.0014)	(0.0015)	(0.0015)	(0.0016)	(0.0014)	(0.0015)	(0.0015)	(0.0016)	(0.0014)	(0.0015)	(0.0015)
Five Largest Banks	-0.0004	0.0037	-0.0068	-0.0042	-0.0007	0.0034	-0.0067	-0.0054	0.0005	0.0050	-0.0063	-0.0050
	(0.0054)	(0.0056)	(0.0051)	(0.0048)	(0.0054)	(0.0056)	(0.0051)	(0.0047)	(0.0053)	(0.0055)	(0.0050)	(0.0047)
Loans-to-Assets	0.0191***	0.0505***	0.0102***	0.0103***	0.0192***	0.0505***	0.0102***	0.0104***	0.0191***	0.0508***	0.0101***	0.0103***
	(0.0049)	(0.0099)	(0.0023)	(0.0022)	(0.0049)	(0.0099)	(0.0023)	(0.0022)	(0.0049)	(0.0099)	(0.0023)	(0.0022)
Deposits-to-Assets	-0.0172	0.0125	-0.0025	-0.0022	-0.0171	0.0124	-0.0025	-0.0016	-0.0174	0.0125	-0.0025	-0.0016
	(0.0142)	(0.0147)	(0.0084)	(0.0085)	(0.0141)	(0.0146)	(0.0084)	(0.0086)	(0.0142)	(0.0147)	(0.0084)	(0.0086)
GDP Growth	0.0742	0.110**	-0.0181	-0.03	0.0729	0.109**	-0.0178	-0.0345	0.0757	0.113**	-0.0176	-0.0343
	(0.0588)	(0.0536)	(0.0314)	(0.0338)	(0.0578)	(0.0527)	(0.0312)	(0.0348)	(0.0590)	(0.0537)	(0.0314)	(0.0350)
Inflation Ratio	-0.0129	-0.0259***	-0.0113	-0.0105	-0.0129	-0.0258***	-0.0112	-0.0118	-0.0127	-0.0258***	-0.0112	-0.0118
	(0.0110)	(0.0098)	(0.0105)	(0.0103)	(0.0109)	(0.0097)	(0.0105)	(0.0103)	(0.0109)	(0.0097)	(0.0104)	(0.0101)

Table 11: (Cont.)

Variable	ATET: Gross Derivatives (Control = 0; Treatment = 1)				ATET: Hedging Derivatives (Control = 0; Treatment = 1)				ATET: Trading Derivatives (Control = 0; Treatment = 1)			
	CRSTE	CRSTE	VRSTE	VRSTE	CRSTE	CRSTE	VRSTE	VRSTE	CRSTE	CRSTE	VRSTE	VRSTE
	(1)	(7)	(4)	(10)	(2)	(8)	(5)	(11)	(3)	(9)	(6)	(12)
Dummy Crisis	0.0194***	0.0160***	0.0139***	0.0136***	0.0193***	0.0159***	0.0139***	0.0135***	0.0194***	0.0159***	0.0139***	0.0136***
	(0.0043)	(0.0039)	(0.0034)	(0.0034)	(0.0043)	(0.0039)	(0.0034)	(0.0034)	(0.0043)	(0.0039)	(0.0034)	(0.0034)
Dummy COVID-19	-0.0060	-0.00605*	-0.0086***	-0.00775**	-0.0061	-0.00612*	-0.0086***	-0.0079**	-0.0060	-0.00604*	-0.0087***	-0.0078**
	(0.0038)	(0.0036)	(0.0032)	(0.0032)	(0.0038)	(0.0035)	(0.0032)	(0.0032)	(0.0038)	(0.0036)	(0.0032)	(0.0032)
Constant	0.348***	-0.606**	0.348***	0.322***	0.345***	-0.607**	0.345***	0.317***	0.346***	-0.609**	0.350***	0.325***
	(0.0390)	(0.2867)	(0.0684)	(0.0505)	(0.0389)	(0.2879)	(0.0685)	(0.0500)	(0.0393)	(0.2863)	(0.0691)	(0.0507)
Fixed Effects	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes
No of Banks	1,175	1,175	1,175	1,175	1,175	1,175	1,175	1,175	1,175	1,175	1,175	1,175
Year	2001-2021	2001-2021	2001-2021	2001-2021	2001-2021	2001-2021	2001-2021	2001-2021	2001-2021	2001-2021	2001-2021	2001-2021
Obs.	17,159	17,159	17,159	17,159	17,159	17,159	17,159	17,159	17,159	17,159	17,159	17,159
Truncated Obs.	14,970	14,970	14,198	14,198	14,970	14,970	14,198	14,198	14,970	14,970	14,198	14,198

Note: This table presents the robustness test results using Difference-in-Differences (DiD) regression, analyzing the Average Treatment Effect on the Treated (ATET) for three types of derivatives: Gross Derivatives, Hedging Derivatives, and Trading Derivatives. The ATET estimates assess the causal impact of each derivative type on bank efficiency by comparing treated groups (banks using derivatives) to control groups (banks not using derivatives). The models control for unobserved heterogeneity using bank-, country-, and time-fixed effects. Standard errors are reported in parentheses and clustered at the bank, country, and year levels to account for potential intra-group correlations. Statistical significance is denoted by ***, **, and * for the 1%, 5%, and 10% levels, respectively. Detailed variable definitions are provided in Table 1.