

**Do climate commitments matter? Financial stability and policy context in the banking
sector**

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ABSTRACT

We examine whether environmentally conscious banks exhibit lower credit risk, addressing a gap in the literature on financial stability. Although curbing carbon emissions depends on financial sector commitment to climate targets, existing studies largely focus on the alignment between environmental behavior and loan portfolios rather than risk outcomes. Analyzing 121 banks across Europe and the United States, we find that greener institutions reduce credit risk following climate policy shocks. Exploiting the Paris Agreement, we analyze how climate regulatory risk affects bank solvency. Results indicate that highly exposed banks face a higher probability of default during periods of heightened policy uncertainty, such as the United States withdrawal from the agreement. This effect is more pronounced among European banks. These findings contribute to discussions regarding the credibility of climate commitments among financial participants.

Keywords: Climate Policy, Transition Risks, Credit Risk, Committed Banks, Financial Stability.

JEL Classification: G20, G21, G28, Q54

Work-in-progress – May 2026

1 Introduction

The 2015 Paris Agreement intensified the global focus on sustainability through binding climate targets. Policymakers promoted adaptation and mitigation regulations on climate change, prompting financial agents to reallocate their capital away from carbon-intensive sectors (Bolton & Kacperczyk, 2023). This immediate awareness highlighted the role of the financial sector in the transition (Chiaramonte et al., 2022). Consequently, several banks adopted voluntary sustainability initiatives to demonstrate their commitments to climate targets (Sastry et al., 2024). An emerging line of research analyzes the effects of signaling an environmentally conscious behavior on financial stability (Chiaramonte et al., 2022). Some studies point to enhanced credit quality among climate-aligned banks (Birindelli et al., 2022), whereas others find no significant differences in performance relative to their counterparts (Malandrakis & Drakos, 2025). This study aims to contribute to this line of research by examining how banks' environmental attitude affects solvency risk¹.

After the introduction of the Paris Agreement, financial institutions adjusted their portfolios, pricing transition risks through a carbon premium (Bolton & Kacperczyk, 2023; Reghezza et al., 2022). However, the position of the financial institutions is not persistent in time, as evidence points to a reversal in moments with heightened climate policy uncertainty, such as the United States withdrawal from the Agreement (Alessi et al., 2024). While several studies analyze whether banks price these climate policy shocks (transition risks) by charging a premium on loan rates, evidence remains limited regarding how exposure to transition risks affects banks' credit risk². Therefore, this study extends the literature by analyzing the impact of the Paris Agreement on financial stability and the subsequent effects of climate policy uncertainty.

¹ Following Degryse et al. (2023), we define 'environmental attitude' as greenness awareness (signaled by participation in voluntary sustainability frameworks) and lower exposure to climate-related risks. Throughout this article we use "environmental attitude", "environmentally conscious banks", and "green banks" interchangeably.

² According to Bolton and Kacperczyk (2023), transition risks reflect financial markets' uncertainty rate of adjustment to a low-carbon economy, include investors' evolving beliefs toward climate change, and incorporate a range of policy intervention shocks.

The study employs panel data on 121 large commercial banks from 2004 to 2024. Out of the sample banks, 57 are domiciled in Europe and 64 in the United States. This geographic selection relies on literature suggesting that firms embedded in stronger social norms are more likely to improve environmental and financial performance (Birindelli et al., 2022; Dyck et al., 2019). We examine financial stability across two contrasting policy contexts: Europe, a region where sustainability is at the core of economic development (Bua et al., 2024), and the United States, where such integration remains voluntary. Comparing the banking sector in similar economies with differing climate commitments offers the advantage of evaluating the feasibility of managing climate-related risks through established capital requirements (Roussel, 2024).

The empirical analysis consists of two parts. First, we assess whether environmentally conscious banks exhibit a lower credit risk by employing a staggered difference-in-differences (DiD) approach to evaluate the adoption of the Equator Principles (EP) (Kacperczyk & Peydró, 2021). Given that European banks dominate our EP sample, we introduce a secondary greenness metric that captures climate-related risk exposure and exploit the Paris Agreement as a quasi-natural experiment using a standard DiD (Reghezza et al., 2022). These estimates reveal that highly exposed banks experience a rise in solvency risk following this policy shock. Second, we study the effects of the U.S. withdrawal from and re-entry into the Paris Agreement on solvency risk by estimating both two-way fixed effects (TWFE) and staggered DiD models (Alessi et al., 2024). We find that highly exposed banks in Europe are more sensitive to these changes than their U.S. counterparts, aligning with the premise that international commitments lack credibility without domestic regulatory enforcement (Bolton & Kacperczyk, 2023).

This study builds upon the banking literature, examining the effects of climate change on financial stability. Birindelli et al. (2022) document a positive association between banks' environmental performance and the credit quality, underscoring the role of institutional context in the relationship. Consistent with this evidence, Chiaramonte et al. (2022) find a negative link between sustainability performance and the credit risk during periods of financial distress, implying that sustainability serves as an 'insurance-like' risk mitigation mechanism. By contrast, Malandrakis and Drakos (2025) show that greener banks differ from non-green banks only during

a financial crisis and in terms of capital and credit risks. Collectively, these findings indicate that banks signaling climate commitment exhibit a lower risk primarily during economic turmoil. This behavior points to pecuniary motivations driving the decision to reflect greener preferences (Demetriades & Politsidis, 2025).

The study contributes to two lines of research. First, it adds to the discussion on the adoption of voluntary sustainability frameworks within the banking sector. Existing literature predominantly examines the alignment between the adoption status and actual lending behavior³. Evidence reveals that signatory banks charge higher loan spreads to carbon-intensive firms for shorter maturities. However, lending volumes to high-emitting sectors remain large, and evidence supporting genuine engagement strategies is limited. (Degryse et al., 2023; Delis et al., 2024; Kacperczyk & Peydró, 2021; Sastry et al., 2024). We complement these findings by redirecting attention toward financial stability. Our results document a risk reduction following the adoption of sustainability initiatives. Viewed alongside the lending behavior literature, these findings indicate that reputational enhancement, rather than strict adherence to climate targets, motivates the participation.

Second, we contribute to the literature evaluation of climate policy implications for the banking sector. Prior studies find that banks adjust their portfolios toward greener assets following the Paris Agreement (Degryse et al., 2023; Delis et al., 2024; Reghezza et al., 2022). Alessi et al. (2024) show that such adjustments may be temporary when policy credibility weakens. We extend this discussion by documenting a positive relationship between climate change exposure and credit risk, particularly in jurisdictions with stricter sustainability regulations. Conversely, highly exposed banks in the U.S. exhibit a deterioration in solvency risk only immediately after the ratification, with effects that dissipate over time despite subsequent policy changes.

Our study provides relevant implications for policymakers, financial institutions, and investors. Policymakers should consider strengthening domestic climate policies to support

³ The adoption of several voluntarily sustainability frameworks, such as: The Principles for Responsible Banking (PRB), the Equator Principles (EP), the Net-Zero Bank Alliance (NZBA), and the Science Based Target Initiative (SBTi).

international commitments across sectors and reduce the risk of disorderly transition. In general, the findings suggest that regulators and central banks should treat climate-related policy risk as a component of financial stability monitoring, not just sustainability reporting. The reported geographical differences imply that a one-size-fits-all policy approach may be ineffective, and that supervisory stress testing should account for regional climate policy sensitivity. In addition, commercial banks could generate value by managing their climate commitments and directly influencing the environmental practices of high-emitting borrowers. Finally, investors can interpret climate alignment as a signal of lower downside risk during policy transitions, thereby reinforcing demand for credible environmental disclosures.

The remainder of this study proceeds as follows. [Section 2](#) reviews the related literature and develops the theoretical framework. [Section 3](#) describes the sample; [Section 4](#) provides the empirical analysis, and [Section 5](#) concludes.

2 Literature Review and Hypotheses Development

Stakeholder theory provides the foundation for understanding how firm operations determine the value creation process beyond profit maximization (Freeman et al., 2004). This framework requires managers to account for all groups with interests tied to the firm's core purpose (Parmar et al., 2010). The transition to a low-carbon economy now compels stakeholders to demand that banks signal climate commitments through responsible practices (Chiaramonte et al., 2022). A signal constitutes an action, unobservable attribute, or characteristic that communicates reliable information to decision-makers, reducing information asymmetries (Connelly et al., 2024). Banking literature identifies several salient signals: the adoption of voluntary sustainability initiatives, such as the Equator Principles (EP) or the Principles for Responsible Banking (PRB) (Delis et al., 2024; Malandrakis & Drakos, 2025), ESG scores (Birindelli et al., 2022; Chiaramonte et al., 2022), and climate-related risk exposure (Alessi et al., 2024; Jung et al., 2025). While the first two categories represent self-selected disclosures, the latter provides an estimation of banks' credit channel exposure to high-emitting firms.

Prior literature links banks' environmental commitments to their financial resilience during exogenous shocks. Several studies document a negative association between banks' ESG performance or environmental scores and credit risk (Birindelli et al., 2022; Chiaramonte et al., 2022). Others caution that such metrics may not fully capture bank lending behavior (Cregan et al., 2024; Giannetti et al., 2023). Consequently, an emerging line of research investigates whether participation in voluntary sustainability initiatives serves as a reliable signal of green alignment by analyzing the credit allocation. Established in 2003 as a baseline standard for environmental and social risk management, the Equator Principles (EP) represent a clear illustration. Signatories to this framework hold a greater proportion of loans in less carbon-intensive firms (Ehlers et al., 2022). Additionally, EP adopters maintain stronger capital adequacy ratios than their non-adopting peers during and after financial crises (Malandrakis and Drakos, 2025). Building upon this empirical foundation, we formulate our first hypothesis as follows:

H₁: After adopting the Equator Principles, environmentally conscious banks exhibit lower credit risk than non-adopting banks.

Although the Equator Principles may provide a reliable signal of environmental attitude, the limited adoption of this initiative among U.S. banks requires alternative measures. Following Alessi et al. (2024), we redefine our greenness indicator to identify banks with higher exposure to climate change risk and examine the effects of the Paris Agreement on their credit risk channel. Jung et al. (2025) posit that high exposure to climate transition risks impairs the capacity for banks to absorb losses during climate stress⁴. In line with this premise, we propose our second hypothesis:

H₂: Following the Paris Agreement, banks with higher climate change exposure experience an increase in credit risk relative to less exposed peers.

From an institutional theory perspective, the Paris Agreement exerts societal pressures on economic agents to actively participate in the decarbonization of the economy (Degryse et al.,

⁴ According to Jung et al. (2025), a climate stress event is a shock affecting to a specific climate risk factor. The authors construct this factor as a synthetic equity portfolio that loses value upon the materialization of climate risks.

2023). This international pan-governmental agreement prompted banks to align their portfolios with greener sectors (Delis et al., 2024; Ehlers et al., 2022; Reghezza et al., 2022). However, Alessi et al. (2024) indicate that this preference was largely transitory. Banks reallocated their holdings toward high-emitting sectors following the 2017 U.S. withdrawal from the Paris Agreement. This climate policy reversal likely exacerbates investors' concerns regarding the credibility and validity of global agreements (Bolton & Kacperczyk, 2023). Given that periods characterized by elevated transition risks, specifically, heightened climate policy uncertainty, are negatively associated with banks' financial stability (Demetriades & Politsidis, 2025; Jung et al., 2025; Martini et al., 2024; Birindelli et al., 2022), we propose a third hypothesis:

H₃: During periods of heightened climate policy uncertainty, banks with higher exposure to transition risks experience a more pronounced increase in solvency risk.

In this context, we define climate policy uncertainty as the uncertainty surrounding changes in environmental policies and other governmental actions that either advance or impede progress towards the objectives of the Paris Agreement (Alessi et al., 2024; Bolton & Kacperczyk, 2023; Gavrilidis, 2021).

3 Data and sample

Our sample comprises commercial banks domiciled in Europe and the United States, spanning the period from 2004 to 2024. The selection of the geographical scope is motivated by prior studies highlighting the influence of cultural and social norms on investors' behavior. Empirical evidence demonstrates that firms operating under stringent climate policies, such as those in member states of the European Union, the European Free Trade Association (EFTA), and the United Kingdom, are more likely to influence the sustainability performance of their holdings (Dyck et al., 2019; Liang & Renneboog, 2016). Conversely, jurisdictions exhibiting lower sustainability performance (i.e., the United States) delay the progress toward carbon neutrality, thereby threatening macroeconomic and financial stability through the credit channel (Birindelli et al., 2022). Comparing these divergent regulatory approaches offers valuable insights

into the ongoing debate regarding the implementation of a green supporting factor (Malandrakis & Drakos, 2025; Oehmke & Opp, 2023; Thomä & Gibhardt, 2019).

We extract financial and accounting data from LSEG Workspace, Orbis, and Bloomberg. We retrieve bank greenness metrics from Sautner et al. (2023) [database](#) and the Equator Principles [portal](#).

We construct an initial dataset of 1,360 banks. Removing duplicates and excluding investment banks, corporate financial services, retail and mortgage banks, reduces the sample to 824 entities. To mitigate measurement error, we require sufficient data on credit risk proxies (i.e., the probability of default) and CAMEL ratios (capital adequacy, asset structure, management, earnings, and liquidity), which further narrows the sample to 234 banks (60 in Europe and 174 in the United States). To account for consolidation, we treat merged banks as separate entities before acquisition and assign all post-merger observations to the acquirer's identifier.

Finally, we remove community banks in the U.S., defined as commercial banks with total assets below \$10 billion (Ebrahim et al., 2025). Similarly, we exclude “small and non-complex institutions” from the European sample. Following Article 4(1) (145) of the Capital Requirements Regulation ([Regulation \(EU\) 2019/876](#)), this classification applies to banks with average total assets equal to or below 5€ billion over the last four years of our analysis (2020-2024). For the United Kingdom, the Prudential Regulation Authority (PRA) sets an equivalent threshold at £4.4 billion ([Prudential Regulation Authority, 2025](#)). The final sample comprises 121 commercial banks, 57 in Europe and 64 in the United States. Table 1 reports the final bank distribution by country.

Insert Table 1

As can be noted from the table, the final European sample consists of observations from 16 countries. The sample includes banks domiciled in 13 different European Union member states, in the EFTA (Norway and Switzerland), and in the United Kingdom.

4 Empirical Analysis

4.1 Descriptive Statistics

Following banking literature, we employ accounting- and market-based variables - Z-Score and the probability of default (*POD*), respectively - as primary indicators of credit risk (Alessi et al., 2024; Laeven & Levine, 2009; Malandrakis & Drakos, 2025). For robustness, we incorporate a measure of systematic risk based on Jung et al.'s (2025) stranded asset factor estimated by climate beta, which proxies the market expectation for future transition risk. Specifically, the climate beta regresses a bank's return sensitivity on a portfolio of climate-related indices. Furthermore, Jung et al. (2025) establish this metric as an alternative indicator of a bank's underlying loan composition. Table 1A in the Appendix details the estimation methodology for each variable.

Table 2 presents the descriptive statistics for our sample, pointing to a generally conservative risk profile. On average, banks exhibit a robust distance to insolvency, evidenced by an average Z-Score of 28.08% (3.07 in logarithmic terms) and a 5-year probability of default of 1.56% (0.29 in logarithmic terms). The climate beta yields a mean of -0.189. Given that the underlying stranded asset factor represents a carbon-intensive portfolio, this negative mean reveals that the average bank moves inversely to fossil fuel shocks, indicating low overall exposure to transition risks.

The main explanatory variables capture banks' environmental profiles. We utilize the adoption status as a signal of environmental behavior, as evidence shows that EP members have a greater proportion of loans in less carbon-intensive firms (Ehlers et al., 2022). EP signatories comprise 14.7% of our sample, of which 89.84% are domiciled in Europe. Considering the limited EP adoption among U.S. institutions, we introduce a supplementary binary indicator denoting whether a bank's overall climate change exposure falls above or below the sample median (Alessi et al., 2024). To proxy this exposure, we employ data from Sautner et al. (2023). This indicator employs a machine-learning algorithm to estimate the relative frequency of climate-related bigrams discussed during quarterly earnings conference calls (Heath et al., 2023; Jung et al., 2025). Our sample yields a mean aggregate climate change exposure of 0.323. While lower than

the Sautner et al.'s (2023) heavily skewed cross-industry mean of 1.01, our sample closely aligns with their median of 0.30, reflecting a relatively modest exposure.

To mitigate omitted variable bias, our empirical models incorporate a vector of bank-level characteristics (Baselga-Pascual et al., 2015; Malandrakis & Drakos, 2025). The sample mean Tier 1 capital ratio is 13.27%, exceeding the 8% Basel Committee III regulatory minimum (Laeven & Levine, 2009). Non-performing loans to total assets (NPL/TA) exhibit an adequate asset quality, averaging 1.89%. Management efficiency, measured by the cost-to-income ratio (*CIR*), averages 60.45%, and profitability remains robust with an average return on equity (ROE) of 9.22%. Liquidity risk is proxied by the loan-to-deposit ratio (*LoanToDeposits*), which yields an average of 1.197. We also control for bank size (total assets), with a mean of \$287 billion (24.52 in logarithmic terms). To account for macroeconomic variation, we include the GDP growth rate (*GGDP*), which averages to 1.45%. All regressions include bank and year fixed effects to control for unobserved heterogeneity. All continuous variables are winsorized at the 1st and 99th percentiles to mitigate the influence of outliers, and logarithmic transformations are applied to risk proxies and total assets to reduce skewness.

Insert Table 2

Table 3 presents the pairwise correlation for the variables in our models. Although EP adopters and bank size correlate at 0.688, a mean variance inflation factor (VIF) of 1.55 (maximum 2.07) confirms that multicollinearity is not a concern. This correlation suggests that larger institutions possess the resources to manage the administrative costs of membership. EP adopters exhibit mixed associations: the variable correlates negatively for both credit measures, the log Z-Score (-0.169), and the probability of default (-0.109). Because these unadjusted pairwise correlations do not account for the confounding effect of bank size, they underscore the need for multivariate fixed-effects models. In addition, EP members are negatively associated with the climate beta (-0.215), indicating lower sensitivity to climate-related market shocks. The correlation between Sautner et al.'s (2023) climate change exposure metric and the climate beta is statistically insignificant (0.025). This absence of a direct link confirms that language-based

metrics capture internal managerial awareness and perceived materiality, while the climate beta reflects market-derived covariance.

Insert Table 3

4.2 Banks' environmental attitude and financial stability

To assess hypothesis 1, we adopt a staggered DiD specification in line with Kacperczyk and Peydró (2021), expressed in Equation 1:

$$y_{b,c,t} = \alpha + \beta_1 EP_{b,t} + \theta Z_{b,t-1} + \delta GGD P_{c,t-1} + \lambda_b + \gamma_t + \varepsilon_{b,c,t} \quad (1)$$

Where $y_{b,c,t}$ is a proxy of credit risk for bank b in country c at year t . $EP_{b,t}$ is a dummy variable that equals 1 in the year t after a bank adopts the Equator Principles, and 0 otherwise. $Z_{b,t-1}$ is a vector of bank-level control variables. We introduce the country-level GDP growth rate ($GGD P_{c,t}$) to account for observed, time-varying macroeconomic conditions. The terms λ_b and γ_t represent bank and year fixed effects, respectively, which absorb unobserved time-invariant bank characteristics and time-varying trends. Standard errors are robust to heteroskedasticity and clustered at the bank level to account for serial correlation within institutions.

The underlying identification assumption is that, absent bank commitment to climate initiatives, the credit risk of both treated and control groups would have behaved similarly; that is, they would have followed parallel trends. Table 4 reports the standard Two-Way Fixed Effects (TWFE) estimates for Equation 1. Variance inflation factor (VIF) analyses confirm the absence of multicollinearity, with model averages of approximately 1.30. Although the coefficients are statistically insignificant across all specifications, their directional sign suggests that EP adoption is associated with lower credit risk. This lack of statistical significance may stem from the aggregation bias inherent in the standard TWFE estimators under staggered treatment timing (Roth et al., 2023). Considering that TWFE calculates a variance-weighted average of all possible two-by-two comparisons, heterogeneous treatment dynamics can cause early-and late-treated group averages to offset one another, potentially attenuating the overall coefficients toward zero.

Insert Table 4

To assess robustness and control for potential aggregation bias, we employ Callaway and Sant’Anna (2021) doubly-robust estimator. Table 5 presents the aggregated dynamic treatment effects (ATT) across all risk proxies (Columns 1 through 3), while Figure 1 illustrates their respective event study plots. Following Alessi et al. (2024), we assume no treatment anticipation and define the control group as never-treated (Assumptions 3 and 4 in Callaway and Sant’Anna (2021)). To satisfy the conditional parallel trends assumption, we employ doubly-robust inverse probability weighting and match on a vector of covariates: capital ratio (*CAR Tier 1*), non-performing loans (*NPL/TA*), cost-to-income, return on equity (*ROE*), loan-to-deposits (*LoanToDeposits*), bank size, and GGDP.

Insert Table 5

Insert Figure 1

The findings indicate an improvement in credit risk following the adoption of the Equator Principles (EP) relative to non-adopters. Consistent with Hypothesis 1, the results for the log Z-Score reveal a post-adoption increase in financial stability, signaling a reduction in insolvency risk. These findings complement those for the log of the probability of default (*log(POD5Y)*), which yields consistent group-specific effects. While the event study plots exhibit some pre-treatment dynamics for the probability of default between 2010 and 2011, these movements likely capture market-wide adjustments to banking regulatory events (Gropp et al., 2019). Given that most EP adopters in our sample are European banks—operating under relatively stringent capital requirements—we extend the definition of environmental commitment to incorporate U.S. banks and evaluate the effects of climate commitment in the context of a global climate policy shock.

Building on climate finance and banking literature, we use the introduction of the Paris Agreement as a quasi-natural experiment. This policy shock affected all sectors, particularly those in carbon-intensive industries. While banks’ direct operational emissions are relatively low, their exposure to climate-related risks materializes indirectly through the credit channel (Degryse et al., 2023b; Delis et al., 2024; Jung et al., 2025; Reghezza et al., 2022). To capture this underlying exposure, we employ Sautner et al.’s (2023) firm-level metrics, which quantify the frequency of climate-related discourse during quarterly earnings conference calls; higher frequencies signal

greater exposure to climate change. Considering this context, we implement a standard DiD approach to test Hypothesis 2, classifying highly exposed banks as the treatment group (Alessi et al., 2024). The empirical model is specified as follows:

$$Y_{b,c,t} = \beta_0 + \beta_1 HCC_b + \beta_2 Post_t + \beta_3 (HCC_b \times Post_t) + \theta Z_{b,t-1} + \delta GDP_{c,t-1} + \lambda_b + \gamma_t + \varepsilon_{b,c,t} \quad (2)$$

Where HCC_b is a time-invariant indicator equal to 1 if a bank's climate exposure exceeds the pre-treatment median, and 0 otherwise. $Post_t$ takes the value of 1 for the years following the 2015 Paris Agreement. The interaction term $HCC_b \times Post_t$ captures the main treatment effect. For brevity, the dependent credit risk proxies ($Y_{b,c,t}$), the vector of lagged control variables ($Z_{b,t-1}$), the lagged GDP growth ($GDP_{c,t-1}$), and the bank (λ_b) and year (γ_t) fixed effects are defined exactly as in Equation 1.

Table 6 presents the static baseline estimations for Equation 2. Consistent with Hypothesis 2, highly exposed banks (HCC_b) in the international sample exhibit a significant increase in solvency risk following the Paris Agreement. Specifically, the interaction term $HCC_b \times Post_t$ in Models 1 and 2 reveals a decline in the log of Z-Score, which is consistent with the results in Models 3 and 4 showing an increase in the probability of default ($\log(POD\ 5Y)$). These findings align with prior literature in banking, suggesting that post-Paris, banks developed a greater awareness of climate-related risks and actively reallocated capital within their loan portfolios (Delis et al., 2024; Ehlers et al., 2022; Reghezza et al., 2022).

Insert Table 6

Table 7 reports the dynamic event-study estimations. Models 1 and 2 satisfy the parallel trends assumption for the three years preceding the event, whereas the climate beta (Model 3) documents anticipatory market behavior. Notably, the dynamic coefficients for the log Z-Score exhibit meaningful fluctuations in statistical significance during the post-treatment period. While solvency risk significantly increases upon the introduction of the Paris Agreement in 2015, this temporarily reappears in 2017 and dissipates again between 2018 and 2019. These variations align closely with the timeline of the U.S. withdrawal from the Agreement in 2017 and the subsequent

announcements regarding its re-entry in 2019. Consistent with Alessi et al. (2024), this pattern indicates that heightened climate policy uncertainty alters market expectations regarding climate-related risks (i.e., transition risks), prompting financial institutions to manage their exposure in response to a shifting geopolitical landscape.

Insert Table 7

4.3 Policy uncertainty and banks' environmental attitude

The U.S. administration's policy reversals regarding the Paris Agreement induced significant uncertainty among financial agents, temporarily undermining the perceived credibility of stringent climate regulations (Alessi et al., 2024). To assess Hypothesis 3, we exploit this regulatory shock by evaluating the differences of the treated units (HCC) at the regional level. Specifically, we divide the data into European (EU) and United States (US) subsamples and estimate Equation 3 independently for each group:

$$Y_{c,b,t} = \beta_0 + \beta_1 HCC_b + \beta_2 PA_In_t + \beta_3 PA_Out_t + \beta_4 PA_Rejoined_t + \beta_5 (HCC_b \times PA_In_t) + \beta_6 (HCC_b \times PA_Out_t) + \beta_7 (LCC_b \times PA_Rejoined_t) + \theta Z_{b,t-1} + \delta GDP_{c,t-1} + \lambda_b + \gamma_t + \varepsilon_{c,b,t} \quad (3)$$

Where PA_In_t is an indicator equal to 1 after 2016, the year the United States officially ratified the Paris Agreement (PA); PA_Out_t takes the value of 1 for the 2017-2020 period, capturing the subsequent withdrawal; $PA_Rejoined_t$ equals 1 from 2021 onward, reflecting the Biden administration's official re-entry into the Agreement. The interaction terms ($HCC_b \times PA_In_t$; $HCC_b \times PA_Out_t$; $HCC_b \times PA_Rejoined_t$) capture the dynamic average treatment effect for the treated units across these regulatory regimes. Consistent with Equations 1 and 2, $Z_{b,t-1}$ represents the vector of lagged bank-level controls and the one-year-lagged GDP growth rate ($GDP_{c,t}$). The terms λ_b and γ_t denote bank and time fixed-effects, accounting for time-invariant bank characteristics and unobserved aggregate time trends, respectively.

Table 8 reports the subsample results for Equation 3. Highly exposed banks (HCC) in the US exhibit a riskier profile during the 2016 ratification of the Paris Agreement and the 2017-2020

withdrawal periods, evidenced by a significant decline in the Z-Score (Model 1) and an increase in the 5-year probability of default (Model 3). The formal re-entry into the Agreement in 2021 (*PA_Rejoined_{it}*) yielded no statistically significant impact on their credit risk. Conversely, highly exposed European banks experienced a significant increase in credit risk during both the U.S. withdrawal and the subsequent re-entry. These dynamics align with Alessi et al. (2024), who find that European financial institutions initially reallocated capital away from highly exposed firms following the Paris Agreement, but reversed these positions amidst subsequent policy shifts and heightened uncertainty. We extend this literature by documenting that this capital reallocation ultimately translated into a higher credit risk.

Insert Table 8

To assess the robustness of our baseline findings against potential weighting biases, we implement a staggered DiD using De Chaisemartin and D'Haultfoeuille's (2024) estimator. Focusing primarily on U.S. *HCC_b* banks and retaining the covariate structure from Equation 3, Table 9 presents the dynamic estimations. Consistent with Table 8, the *did_multiplegt_dyn* estimator reveals that, on average, these climate policy shocks did not yield a statistically significant persistent shift in the credit risk profile of highly exposed banks. However, we observe a significant positive effect during the third period (*Effect_3*) for the climate beta, indicating an elevation in systematic climate risks. Furthermore, the dynamic results for the log Z-Score (Model 1) should be interpreted with caution, as the significant placebo estimate indicates a violation of the parallel trends assumption.

The findings support Hypothesis 3 only when considering the climate policy stringency at the country level. From an institutional theory perspective, the divergence in our regional findings suggests that markets price this uncertainty based on domestic policy stringency, highlighting the role of policymakers in operationalizing broad international agreements into granular, enforceable regulations (Bolton & Kacperczyk, 2023).

Insert Table 9

4.3 Limitations

These findings are subject to several empirical limitations. Concurrent macroeconomic events, such as the European sovereign debt and global financial crises, coincide with the sample period, potentially confounding the identification strategy and restricting causal inference. This exogenous volatility, combined with a limited sample of bank-year observations, attenuates statistical power. While the implementation of Callaway and Sant’Anna (2021) and De Chaisemartin and D’Haultfoeuille (2024) estimators mitigates staggered weighting biases, these robust approaches exacerbate the bias-variance tradeoff. For the EP analysis (Callaway & Sant’Anna, 2021), restricting the control group to never-treated units reduces the effective sample size, thereby inflating the standard errors of the Average Treatment Effect on the Treated (ATT) estimates. Similarly, the De Chaisemartin and D’Haultfoeuille (2024) framework constrains the identification of treatment-switching dynamics over narrow windows, such as the 2016-2017 transition.

Data granularity and geographic scope further circumscribe the analysis. The reliance on annual bank-level aggregates prevents a high-frequency assessment of banks’ environmental behavior. Access to granular, quarterly loan-level data would enable a more precise indicator of banks’ exposure to carbon-intensive sectors. Future research could refine the analysis by distributing the sample between the borrowers’ industry or by quantiles based on the unit-level carbon emissions. This approach for asset classification could provide a more consistent definition of what constitutes “green” assets, given the limited precision of existing taxonomies (Thomä & Gibhardt, 2019). Finally, the sample focuses on banks in the United States and Europe, capturing regions with similar economic characteristics but differing sustainability mandates. Expanding the geographic scope would clarify how varying institutional pressures influence the environmental behavior of financial institutions.

5 Conclusions and Discussion

This study examines how banks' environmental attitudes and climate policy implications influence financial stability. We show that banks signaling their environmental engagement by adopting the Equator Principles (EP) experience a reduction in credit risk. Given that most EP signatories in our sample are European banks, we also incorporate a broader measure of climate change exposure (physical and transition risks) to account for jurisdictions with weaker sustainability regulations (Dyck et al., 2019). Exploiting the Paris Agreement as a quasi-natural experiment, we find that banks with greater exposure to climate change risks exhibit higher solvency risk following the climate policy shock in both regions. This evidence is consistent with previous literature suggesting that heightened climate-policy awareness can induce capital reallocation (Delis et al., 2024; Ehlers et al., 2022; Reghezza et al., 2022).

To assess whether these risk profiles persist during periods of elevated climate policy uncertainty, we examine the effects of the U.S. withdrawal from and re-entry into the Paris Agreement. Our results indicate that European banks are more sensitive to these policy fluctuations than their U.S. counterparts. Consistent with institutional theory, one interpretation for the reported findings is that banks operating in countries with stronger social norms face greater pressure to signal alignment with climate commitments and comply with local sustainability policies. This pattern may help explain the lower participation of U.S. financial institutions in the Equator Principles. From a stakeholder theory perspective, these findings suggest that U.S. banks place greater emphasis on financial performance than on stakeholder-oriented objectives, which could be associated with adverse environmental externalities.

Building on the cross-regional variations in transition risk responsiveness, our findings provide critical insights for the global coordination of regulatory frameworks. For policymakers, the results highlight the relevance of harmonizing the stringency of sustainability regulations to prevent cross-border discrepancies. Currently, among the 194 signatories of the Paris Agreement, European nations demonstrate active engagement through mandatory regulation, whereas the stringency varies across other jurisdictions. Such divergence may enable high-emitting firms to seek financing in regions with less stringent standards. For countries leading the transition, the

results may also inform the evaluation of higher capital requirements for non-green banks. This approach aligns with the Brown Penalizing Factor (BPF) introduced by the European Commission in the 2018 action plan “Financing Sustainable Growth” (Thomä & Gibhardt, 2019). The BPF proposes higher capital requirements for “dirty loans”, although research indicates such measures may not directly curb greenhouse gas emissions (Oehmke & Opp, 2023).

Our findings indicate that climate commitments matter for large commercial banks primarily within jurisdictions enforcing stringent sustainability mandates. The motivation for banks to signal environmentally conscious behavior likely reflects external societal pressures rather than an intrinsic pursuit of climate targets. Without synchronized implementation, whereby Agreement signatories adopt uniform mandatory standards locally, the global transition to decarbonization loses credibility. For the financial sector, this lack of coordination decouples global credit demand from regional sustainability compliance. These dynamics present critical implications across financial market participants. Regulators and central banks should integrate transition risks into financial stability monitoring while adapting supervisory stress tests to regional policy sensitivities. For commercial banks, the results underscore the advantage of prioritizing active borrower engagement to influence corporate environmental behavior, which proves more resilient than passive portfolio reweighting. Ultimately, given that climate alignment signals downside protection during policy shifts, markets require credible environmental disclosures to validate these commitments.

6 Reference

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7 Tables

Table 1: Number of banks by country

Country	Number of banks	Freq.	Percent	Cum.
	(1)	(2)	(3)	(4)
Austria	4	84	3.31	3.31
Belgium	1	21	0.83	4.13
Denmark	3	63	2.48	6.61
Finland	3	63	2.48	9.09
France	11	231	9.09	18.18
Germany	2	42	1.65	19.83
Greece	1	21	0.83	20.66
Ireland	2	42	1.65	22.31
Italy	3	63	2.48	24.79
Netherlands	2	42	1.65	26.45
Norway	6	126	4.96	31.40
Poland	1	21	0.83	32.23
Spain	3	63	2.48	34.71
Sweden	3	63	2.48	37.19
Switzerland	4	84	3.31	40.50
United Kingdom	8	168	6.61	47.11
United States	64	1,344	52.89	100.00
Total	121	2,541	100.00	

This table presents the distribution of large commercial banks by country in the final sample, totaling 121 entities. Column 2 presents the number of observations per country, while column 3 shows their proportion over the total amount. The sample includes banks domiciled in European Union member states, the European Free Trade Association (EFTA), mainly Norway and Switzerland, the United Kingdom, and the United States. The data was sourced from LSEG Workspace, Orbis, and Bloomberg, reflecting the final sample after the data curation process.

Table 2: Summary Statistics

Variables	Obs	Mean	Std. Dev.	Min	Max
<i>Banks risk</i>					
Z-Score (%)	2,292	28.077	20.377	3.384	90.179
log z bank w	2,292	3.068	.758	1.219	4.502
Probability of default (5Y%)	2,365	1.555	1.034	.303	7.483
log(Probability of default (5Y%))	2,365	.294	.522	-1.194	2.013
Climate Beta	1,790	-.189	.253	-.944	.377
<i>Sustainability Commitment</i>					
Equator Principles (EP)	2,541	.147	.354	0	1
Climate change exposure	1,529	.323	.465	0	2.783
<i>Bank characteristics</i>					
Capital Adequacy Ratio Tier 1 (%)	2,332	13.271	3.98	6.39	28.3
Non-Performing Loans to Total Assets (NPL /TA %)	2,325	1.886	2.329	.04	15.58
Cost-to-income (CIR %)	2,144	60.451	10.934	33.973	95.313
Return on Equity (ROE%)	2,462	9.218	7.479	-26.11	27.22
Loan to Deposits	2,471	1.197	.657	.466	3.825
Total Assets (USD)	2,481	287.0x10 ⁹	602.0x10 ⁹	1.919x10 ⁹	2.841x10 ¹²
Bank Size (log(Total Assets))	2,481	24.516	1.925	21.375	28.675
<i>Country-level characteristics</i>					
GDP growth rate (GGDP %)	2,520	1.454	2.296	-7.441	7.382

This table presents the descriptive statistics for the variables used in the analysis. The dependent variables include the logarithm of Z-Score, the probability of default (*POD 5Y*) in logarithmic terms, and banks' climate beta. Banks' environmental attitude is captured through their adoption status of the Equator Principles (EP) and their exposure to climate change. Bank-level characteristics are CAMEL indicators, such as the capital adequacy (*CAR Tier 1*), non-performing loans to total assets (*NPL/TA*), cost-to-income (*CIR*), return on equity (*ROE*), loan to deposits, and bank size (log of total assets). To control for macroeconomic variations at the country-level, we include the Gross Domestic Product growth rate (*GGDP*). All continuous variables were winsorized at the 1st and 99th percentiles, and dependent variables were log-transformed to enhance right skewness.

Table 3: Correlation Matrix

Variables	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)	(9)	(10)	(11)	(12)
(1) log(Z-Score)	1.000											
(2) log(ProbDefault5Y)	-0.161*** (0.000)	1.000										
(3) Climate beta	0.170*** (0.000)	-0.163*** (0.000)	1.000									
(4) Equator Principles	-0.169*** (0.000)	-0.109*** (0.000)	-0.215*** (0.000)	1.000								
(5) Climate Change Exposure	0.038 (0.152)	-0.022 (0.405)	0.025 (0.371)	0.053** (0.040)	1.000							
(6) CAR Tier 1	0.107*** (0.000)	-0.131*** (0.000)	-0.075*** (0.002)	0.074*** (0.000)	0.100*** (0.000)	1.000						
(7) NPL/TA	-0.270*** (0.000)	0.208*** (0.000)	-0.208*** (0.000)	0.224*** (0.000)	0.078*** (0.003)	0.029 (0.172)	1.000					
(8) Cost-to-income	-0.121*** (0.000)	0.194*** (0.000)	-0.018 (0.463)	0.063*** (0.003)	-0.021 (0.428)	-0.098*** (0.000)	0.209*** (0.000)	1.000				
(9) ROE	0.124*** (0.000)	-0.421*** (0.000)	0.193*** (0.000)	-0.062*** (0.002)	0.016 (0.538)	-0.074*** (0.000)	-0.364*** (0.000)	-0.527*** (0.000)	1.000			
(10) Loan to Deposits	0.073*** (0.000)	-0.313*** (0.000)	-0.146*** (0.000)	-0.023 (0.257)	-0.112*** (0.000)	0.174*** (0.000)	-0.005 (0.804)	-0.205*** (0.000)	-0.058*** (0.004)	1.000		
(11) Bank Size	-0.302*** (0.000)	-0.091*** (0.000)	-0.119*** (0.000)	0.688*** (0.000)	0.054** (0.034)	-0.018 (0.398)	0.284*** (0.000)	0.096*** (0.000)	-0.068*** (0.001)	0.001 (0.953)	1.000	
(12) GGDP	-0.005 (0.811)	-0.305*** (0.000)	0.291*** (0.000)	-0.033* (0.093)	0.035 (0.172)	0.003 (0.876)	-0.077*** (0.000)	-0.040* (0.066)	0.277*** (0.000)	-0.021 (0.299)	0.015 (0.443)	1.000

This table presents Pearson correlation coefficients among the variables used in the analysis. The dependent variables include the logarithm of Z-Score, the probability of default (*POD 5Y*) in logarithmic terms, and banks' climate beta. Banks' environmental attitude is captured through their adoption status of the Equator Principles (EP) and their exposure to climate change. Bank-level characteristics are CAMEL indicators, such as the capital adequacy (*CAR Tier 1*), non-performing loans to total assets (*NPL/TA*), cost-to-income (*CIR*), return on equity (*ROE*), loan to deposits, and bank size (log of total assets). To control for macroeconomic variations at the country-level, we include the Gross Domestic Product growth rate (*GGDP*). P-values are reported in parentheses. Statistical significance is denoted at 1%, 5%, and 10% levels, using ***, **, and *, respectively. All continuous variables were winsorized at the 1st and 99th percentiles. The sample covers yearly data from 2004 to 2024.

Table 4: Two-Way Fixed Effects (TWFE) Staggered Difference-in-Differences.

VARIABLES	$\log(\text{Z-Score})_{b,t}$ (1)	$\log(\text{POD5Y})_{b,t}$ (2)	Climate Beta $_{b,t}$ (3)
EP $_{b,t}$	0.002 (0.077)	-0.041 (0.151)	-0.086 (0.056)
CAR_Tier1 $_{b,t-1}$	0.010*** (0.003)	-0.016*** (0.005)	-0.008** (0.003)
NPL/TA $_{b,t-1}$	-0.011** (0.005)	0.040*** (0.007)	0.005 (0.006)
Cost-to-Income $_{b,t-1}$	-0.003*** (0.001)	-0.003* (0.001)	0.001 (0.001)
ROE $_{b,t-1}$	0.002 (0.002)	-0.012*** (0.002)	0.006*** (0.001)
Loan to Deposits $_{b,t-1}$	0.068 (0.068)	-0.043 (0.062)	-0.024 (0.027)
Bank_Size $_{b,t-1}$	0.006 (0.033)	0.013 (0.033)	0.079*** (0.023)
GGDP $_{c,t-1}$	-0.000 (0.004)	-0.010** (0.005)	0.001 (0.003)
Constant	2.943*** (0.832)	0.553 (0.913)	-2.067*** (0.594)
Observations	1,718	1,788	1,568
R-squared	0.967	0.746	0.610
Bank Fixed Effects	Yes	Yes	Yes
Year Fixed Effects	Yes	Yes	Yes
Standard errors cluster by	Bank	Bank	Bank

This table reports estimates from a staggered difference-in-differences (DiD) specification examining the effects of adopting the Equator Principles on credit risk. The dependent variables include the logarithm of Z-Score, the probability of default (*POD 5Y*) in logarithmic terms, and banks' climate beta. EP is a dummy variable equal to one in the years following a bank's adoption of the Equator Principles. Bank-level corresponds to CAMEL indicators, including capital adequacy (*CAR Tier 1*), non-performing loans to total assets (*NPL/TA*), cost-to-income (*CIR*), return on equity (*ROE*), loan to deposits, and bank size (log of total assets). To account for macroeconomic conditions, we include country-level Gross Domestic Product growth rate (*GGDP*). All continuous variables are winsorized at the 1st and 99th percentiles and log-transformed where applicable. All specifications include banks and year fixed effects. Standard Errors are clustered at the bank level. The sample covers from 2004 to 2024. Statistical significance at the 1%, 5%, and 10% levels is denoted by using ***, **, and *, respectively

Table 5: Doubly-Robust Callway and Sant’Anna (2021) estimators - Staggered Difference-in-Differences

Parameters	$\log(\text{Z-Score})_{b,t}$ (1)	$\log(\text{POD5Y})_{b,t}$ (2)	Climate Beta _{b,t} (3)
<i>Panel A: Single Parameters</i>			
Simple weighted average (ATT)	0.462* (0.186)	-0.321 (0.198)	0.039 (0.045)
Group-specific effects	0.362*** (0.082)	-0.250** (0.093)	0.039 (0.045)
Calendar time effects	0.484** (0.156)	-0.351 (0.193)	0.039 (0.045)
Event study: Pre-average	-0.018 (0.027)	-0.160** (0.059)	0.002 (0.078)
Event study: Post-average	0.529*** (0.151)	-0.349 (0.182)	0.039 (0.045)
<i>Panel B: Partially aggregated parameters</i>			
Group-specific effects			
G2007	0.860*** (0.107)	-0.775** (0.244)	
G2008	0.111 (0.158)	-0.014 (0.086)	
G2019	0.003 (0.024)	0.092 (0.063)	0.039 (0.045)

This table presents estimates from a staggered difference-in-differences (DiD) specification using the doubly robust estimators of Callway and Sant’Anna (2021). Panel A summarizes the average treatment on the treated (ATT), including the simple weighted average, group-specific effects, calendar time effects, and the pre-and post-treatment averages of the event study. Panel B reports group-specific effects by cohort year. The dependent variables include the logarithm of Z-Score, the probability of default (*POD 5Y*) in logarithmic terms, and banks’ climate beta. *P* is a dummy variable equal to one in the years following a bank’s adoption of the Equator Principles. The sample is constructed using matching on a set of covariates, including CAMEL indicators: capital adequacy (*CAR Tier 1*), non-performing loans to total assets (*NPL/TA*), the cost-to-income ratio (*CIR*), return on equity (*ROE*), the loan-to-deposits ratio, and bank size (log of total assets). Macroeconomic conditions are captured by country-level GDP growth (*GGDP*). The sample covers from 2004 to 2024. Statistical significance at the 1%, 5%, and 10% levels is denoted by using ***, **, and *, respectively

Table 6: Standard Difference-in-Differences – 2015 Paris Agreement

VARIABLES	log(Z-Score) _{b,t}		log(POD5Y) _{b,t}		Climate Beta _{b,t}	
	(1)	(2)	(3)	(4)	(5)	(6)
HCC _b x Post _t	-0.088*	-0.104***	0.115**	0.125***	-0.003	-0.019
	(0.046)	(0.033)	(0.044)	(0.041)	(0.026)	(0.022)
CAR_Tier1 _{b,t-1}		0.008**		-0.014**		-0.004
		(0.004)		(0.006)		(0.003)
NPL/TA _{b,t-1}		-0.013**		0.043***		0.008
		(0.006)		(0.009)		(0.007)
Cost-to-Income _{b,t-1}		-0.003**		-0.001		0.001
		(0.001)		(0.002)		(0.001)
ROE _{b,t-1}		0.002		-0.012***		0.005***
		(0.002)		(0.002)		(0.001)
Loan to Deposits _{b,t-1}		0.128		0.063		0.064
		(0.079)		(0.114)		(0.064)
Bank_Size _{b,t-1}		0.017		-0.010		0.062**
		(0.038)		(0.036)		(0.030)
GGDP _{c,t-1}		0.002		-0.006		0.009*
		(0.006)		(0.007)		(0.005)
Constant	2.985***	2.580**	0.373***	0.842	-0.193***	-1.853**
	(0.012)	(0.994)	(0.011)	(0.915)	(0.008)	(0.766)
Observations	1,457	1,218	1,365	1,285	1,265	1,149
R-squared	0.943	0.963	0.810	0.755	0.586	0.637
Bank Fixed Effects	Yes	Yes	Yes	Yes	Yes	Yes
Year Fixed Effects	Yes	Yes	Yes	Yes	Yes	Yes
Standard errors cluster by	Bank	Bank	Bank	Bank	Bank	Bank

This table reports baseline static estimates from a difference-in-differences (DiD) specification corresponding to Equation (2). The dependent variables are the logarithm of the Z-Score, the logarithm of the probability of default (*POD* 5Y), and banks' climate beta. *HCC* identifies banks with high exposure to climate-related risks (above the median), and *Post* is a dummy variable equal to one in the years following the Paris Agreement. The interaction term (*HCC* × *Post*) captures the differential effect of the policy shock on highly exposed banks. Bank-level controls correspond to CAMEL indicators, including capital adequacy (*CAR* Tier 1), non-performing loans to total assets (*NPL/TA*), the cost-to-income ratio (*CIR*), return on equity (*ROE*), the loan-to-deposits ratio, and bank size (log of total assets). Macroeconomic conditions are captured by country-level GDP growth (*GGDP*). All specifications include bank and year fixed effects. Standard errors are clustered at the bank level. The sample spans 2004–2024. Statistical significance at the 1%, 5%, and 10% levels is indicated by ***, **, and *, respectively.

Table 7: Robustness – Parallel Trend Assumption

VARIABLES	$\log(\text{Z-Score})_{b,t}$ (1)	$\log(\text{POD5Y})_{b,t}$ (2)	Climate Beta $_{b,t}$ (3)
Pre-event ($t=-5$) 2010	0.035 (0.039)	-0.105* (0.061)	0.007 (0.050)
Pre-event ($t=-4$) 2011	0.044 (0.041)	-0.154** (0.073)	-0.038 (0.063)
Pre-event ($t=-3$) 2012	0.036 (0.041)	-0.058 (0.055)	-0.057 (0.059)
Pre-event ($t=-2$) 2013	0.024 (0.026)	0.002 (0.055)	-0.090* (0.053)
Paris Agreement ($t=0$) 2015	-0.071*** (0.021)	0.052 (0.057)	-0.057 (0.041)
Post-event ($t=+1$) 2016	-0.028 (0.034)	0.022 (0.065)	-0.052 (0.052)
Post-event ($t=+2$) 2017	-0.054* (0.032)	0.089 (0.053)	-0.068 (0.045)
Post-event ($t=+3$) 2018	-0.050 (0.035)	0.011 (0.059)	-0.016 (0.051)
Post-event ($t=+4$) 2019	-0.049 (0.036)	0.056 (0.062)	-0.107* (0.055)
Post-event ($t=+5$) 2020	-0.096** (0.042)	0.047 (0.065)	-0.027 (0.048)
CAR_Tier1 $_{b,t-1}$	0.008** (0.004)	-0.013** (0.006)	-0.004 (0.003)
NPL/TA $_{b,t-1}$	-0.013** (0.006)	0.043*** (0.009)	0.008 (0.007)
Cost-to-Income $_{b,t-1}$	-0.003** (0.001)	-0.001 (0.002)	0.001 (0.001)
ROE $_{b,t-1}$	0.002 (0.002)	-0.012*** (0.002)	0.005*** (0.001)
Loan to Deposits $_{b,t-1}$	0.129* (0.077)	0.073 (0.112)	0.054 (0.062)
Bank_Size $_{b,t-1}$	0.016 (0.038)	-0.010 (0.036)	0.062** (0.029)
GDP $_{c,t-1}$	0.002 (0.006)	-0.006 (0.007)	0.008* (0.005)
Constant	2.590** (0.987)	0.835 (0.912)	-1.828** (0.756)
Observations	1,218	1,285	1,149
R-squared	0.963	0.757	0.641
Bank Fixed Effects	Yes	Yes	Yes
Year Fixed Effects	Yes	Yes	Yes
Standard errors cluster by	Bank	Bank	Bank

This table reports robustness tests of the parallel trends assumption using an event-study specification. The dependent variables are the logarithm of the Z-Score, the logarithm of the probability of default (*POD 5Y*), and banks' climate beta. The specification includes a series of leads and lags relative to the Paris Agreement, where $t = 0$ corresponds to 2015. Pre-event coefficients ($t = -5$ to $t = -1$) capture dynamics before the policy shock, while post-event coefficients ($t = +1$ to $t = +5$) trace the evolution of the effects thereafter. Bank-level controls correspond to CAMEL indicators, including capital adequacy (*CAR Tier 1*), non-performing loans to total assets (*NPL/TA*), the cost-to-income ratio (*CIR*), return on equity (*ROE*), the loan-to-deposits ratio, and bank size (log of total assets). Macroeconomic conditions are captured by country-level GDP growth (*GGDP*). All specifications include bank and year fixed effects. Standard errors are clustered at the bank level. The sample spans 2004–2024. Statistical significance at the 1%, 5%, and 10% levels is indicated by ***, **, and *, respectively.

Table 8: Paris Agreement and US withdrawal

VARIABLES	log(Z-Score) _{b,t}		log(POD5Y) _{b,t}		Climate Beta _{b,t}	
	US (1)	EU (2)	US (3)	EU (4)	US (5)	EU (6)
High_CC _b x PA_In _t	-0.044* (0.026)	0.076 (0.089)	0.079 (0.062)	0.133 (0.103)	-0.072** (0.034)	0.128** (0.057)
High_CC _b x PA_Out _t	-0.039 (0.032)	-0.069* (0.038)	0.080** (0.035)	0.231* (0.114)	-0.023 (0.022)	0.004 (0.045)
High_CC _b x PA_Rejoined _t	-0.015 (0.042)	-0.192*** (0.059)	0.052 (0.041)	0.244** (0.102)	-0.003 (0.023)	0.037 (0.065)
CAR_Tier1 _{b,t-1}	0.016*** (0.004)	0.004 (0.004)	-0.019*** (0.005)	-0.030** (0.013)	-0.001 (0.004)	0.002 (0.005)
NPL/TA _{b,t-1}	-0.028*** (0.009)	-0.008 (0.007)	0.051*** (0.010)	0.024*** (0.009)	-0.005 (0.008)	0.005 (0.004)
Cost-to-Income _{b,t-1}	-0.002 (0.002)	-0.000 (0.002)	-0.002 (0.002)	-0.003 (0.004)	0.002 (0.001)	-0.002 (0.001)
ROE _{b,t-1}	0.004* (0.002)	-0.000 (0.003)	-0.011*** (0.002)	-0.006 (0.005)	0.005*** (0.002)	0.001 (0.001)
Loan to Deposits _{b,t-1}	0.224** (0.111)	0.094 (0.088)	-0.227* (0.129)	0.088 (0.131)	-0.082 (0.083)	-0.024 (0.068)
Bank_Size _{b,t-1}	0.113*** (0.034)	-0.325*** (0.093)	-0.046 (0.038)	-0.030 (0.153)	0.007 (0.033)	-0.059 (0.078)
GGDP _{c,t-1}	0.000 (0.000)	0.000 (0.004)	0.000 (0.000)	-0.001 (0.007)	0.000 (0.000)	0.001 (0.004)
Constant	0.165 (0.896)	11.365*** (2.425)	2.137** (0.999)	1.400 (4.001)	-0.356 (0.869)	1.373 (2.129)
Observations	865	353	917	368	791	358
R-squared	0.971	0.887	0.821	0.648	0.733	0.652
Bank Fixed Effects	Yes	Yes	Yes	Yes	Yes	Yes
Year Fixed Effects	Yes	Yes	Yes	Yes	Yes	Yes
Standard errors cluster by	Bank	Bank	Bank	Bank	Bank	Bank

This table reports estimates from a two-way fixed effects (TWFE) specification examining the impact of climate policy regimes on bank risk. The dependent variables are the logarithm of the Z-Score, the logarithm of the probability of default (POD 5Y), and banks' climate beta. The analysis distinguishes between U.S. and European banks. *PA_In* is an indicator equal to one from 2016 onward, corresponding to the ratification of the Paris Agreement. *PA_Out* equals one during the 2017–2020 period, capturing the U.S. withdrawal, and *PA_Rejoined* equals one from 2021 onward, reflecting the re-entry into the Agreement. *HCC* equals one when a bank's climate change exposure is above the

median. The interaction terms ($HCC \times PA_In$, $HCC \times PA_Out$, $HCC \times PA_Rejoined$) capture the dynamic average treatment effects across these policy regimes. Bank-level controls correspond to CAMEL indicators, including capital adequacy ($CAR\ Tier\ 1$), non-performing loans to total assets (NPL/TA), the cost-to-income ratio (CIR), return on equity (ROE), the loan-to-deposits ratio, and bank size (log of total assets). Macroeconomic conditions are captured by country-level GDP growth ($GGDP$). All specifications include bank and year fixed effects. Standard errors are clustered at the bank level. The sample spans 2004–2024. Statistical significance at the 1%, 5%, and 10% levels is indicated by ***, **, and *, respectively.

Table 9: Paris Agreement and US withdrawal - Staggered Difference-in-Differences analysis

	(1) log(Z-Score)	(2) log(POD5Y)	(3) Climate Beta
Effect_1	-0.00791 (0.0199)	0.0168 (0.0478)	-0.0198 (0.0407)
Effect_2	-0.0178 (0.0266)	0.0131 (0.0572)	-0.00779 (0.0381)
Effect_3	-0.0123 (0.0361)	0.00689 (0.0474)	0.0754** (0.0269)
Effect_4	0.0224 (0.0430)	0.0409 (0.0540)	-0.00118 (0.0431)
Effect_5	0.0152 (0.0487)	-0.00884 (0.0702)	0.0780 (0.0649)
Placebo_1	0.0634*** (0.0167)	-0.00246 (0.0501)	0.0327 (0.0447)
Placebo_2	0.124*** (0.0347)	-0.0269 (0.0725)	-0.0480 (0.0414)
Placebo_3	0.125* (0.0498)	0.0156 (0.0761)	0.0296 (0.0537)
Placebo_4	0.124* (0.0514)	-0.129 (0.0692)	0.0633 (0.0573)
Placebo_5	0.109* (0.0488)	-0.267* (0.109)	0.114 (0.0702)
Average Cumulative Effect	-0.000153 (0.155)	0.0689 (0.213)	0.125 (0.167)

This table reports estimates from the staggered difference-in-differences (DiD) estimator proposed by De Chaisemartin and D'Haultfoeuille (2024), for the U.S. subsample. The results indicate no statistically significant effects on market-based measures of solvency risk. By contrast, the climate beta exhibits a delayed response, with a significant effect emerging approximately three periods after changes in climate policy. The estimated average cumulative effect attenuates over time. The sample covers the period from 2004 to 2024. Statistical significance at the 1%, 5%, and 10% levels is denoted by using ***, **, and *, respectively.

8 Figures

Figure 1: Equator Principles Adoption effects on solvency and credit risks

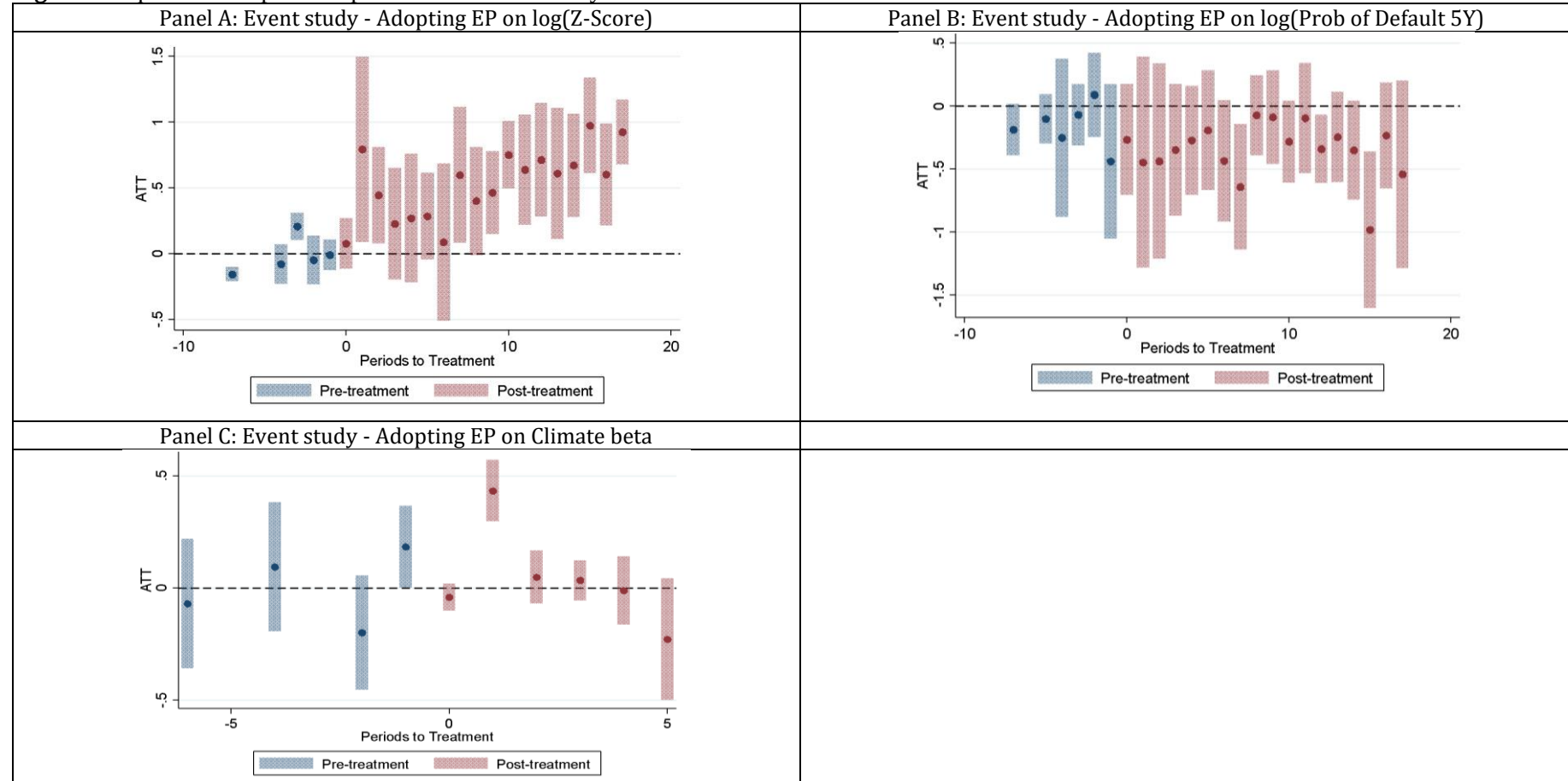


Figure 1 presents dynamic average treatment effects on the treated (ATT) associated with the adoption of the Equator Principles (EP), estimated using the Callaway and Sant'Anna (2021) approach. Panel A reports results for the logarithm of the Z-Score, Panel B for the logarithm of the probability of default (*POD* 5Y), and Panel C for banks' climate beta. The horizontal axis denotes event time relative to EP adoption ($t = 0$), while the vertical axis reports ATT estimates. Pre-treatment coefficients (blue) capture dynamics prior to adoption, and post-treatment coefficients (red) trace the evolution of effects thereafter. Confidence intervals are displayed around point estimates

9 Appendix

Table 1A: Variable Description

Variable type	Variable Name	Description	Source	Literature
Dependent variable	Z-Score ($\log(\text{Z-Score})$)	This variable captures insolvency risk and is calculated as the sum of the return on assets (ROA) and the equity-to-assets ratio (Eq/TA), scaled by the standard deviation of the return on assets ($\sigma(ROA)$) $Z - Score_{i,t} = \frac{ROA_{i,t} + (\frac{Equity}{Total Assets})_{i,t}}{\sigma(ROA_{i,t})}$	LSEG Workspace Authors	Baselga-Pascual et al. (2015) Laeven & Levine, (2009) Demirgüç-Kunt & Huizinga (2010) Palvia et al. (2020) Ebrahim et al. (2025)
	Probability of Default 5 years ($\log(POD5Y)$)	Market-implied probability that the bank defaults within five years, derived from Bloomberg's DRSK model (contingent claims analysis combining market and balance-sheet inputs). Used in logarithmic form.	Bloomberg	Alessi et al. (2024)
	Climate beta	Following Jung et al. (2025), we estimate the climate beta by regressing daily expected bank returns on the return of a carbon portfolio, which acts as a stranded asset factor. The authors construct this synthetic portfolio using a 70% long position in the VanEck Vectors Coal ETF (KOL), a 30% long in the Energy Select Sector SPDR (XLE), and a short position in the S&P 500 ETF Trust (SPY). To adapt this methodology for an international sample, we replace the SPY with the MSCI All Country World Index (ACWI). Additionally, we substitute the XLE with the MSCI ACWI Energy Index, which demonstrates a 0.907 correlation with the XLE.	LSEG Workspace Authors	Jung et al. (2025)
Explanatory variable	Equator Principles (EP)	Binary indicator equal to 1 in bank-year observations where the bank is an active signatory of the Equator Principles, and 0 otherwise. The EP framework is a voluntary risk-management standard for identifying, assessing, and managing environmental and social risks in project finance.	Equator Principles Report	Malandrakis & Drakos (2025) Delis et al. (2024)
	Climate Change Exposure	Aggregate climate change exposure score from Sautner et al. (2023), constructed via a machine-learning keyword discovery algorithm applied to quarterly earnings conference call transcripts. Measures the relative frequency of climate-related	Sautner et al. (2023)	Sautner et al. (2023) Jung et al. (2025)

		bigrams; higher values indicate greater managerial engagement with climate issues.		
	Highly Exposed banks to climate change (<i>HCC</i>)	This variable takes the value of 1 when a fund has been classified as Article 9 exclusively.	Sautner et al. (2023) Authors	Alessi et al. (2024)
	Post	This is a binary variable that takes the value of 1 after the 2015 Paris Agreement introduction.	Authors	Reghezza et al. (2022)
	Post × <i>HCC</i>	This represents the interaction term between highly exposed banks (<i>HCC</i>) and the post-Paris Agreement (<i>PA</i>) period. It is central for the difference-in-differences analysis, as it captures the estimated treatment effect of the Paris Agreement intervention relative to the counterfactual (<i>LCC</i>).	Authors	Alessi et al. (2024)
	Paris Agreement In (<i>PA_In</i>)	A dummy variable that takes the value of 1 after 2016, when the PA became effective for the United States, and 0 otherwise.	Authors	Alessi et al. (2024)
	Paris Agreement Out (<i>PA_Out</i>)	This is a binary variable that takes the value of 1 after the 2017 U.S. withdrawal from the Agreement, and 0 otherwise.	Authors	Alessi et al. (2024)
	Paris Agreement Rejoined (<i>PA_Rejoined</i>)	This is a binary variable that takes the value of 1 after the 2021 U.S. re-entry to the Agreement, and 0 otherwise.	Authors	Alessi et al. (2024)
Control variable	Capital Adequacy Ratio Tier 1	Tier 1 capital divided by risk-weighted assets, expressed as a percentage. Tier 1 capital consists primarily of common equity, retained earnings, and qualifying reserves. Higher values indicate greater loss-absorption capacity. The Basel III minimum is 8%.	LSEG Workspace	Birindelli et al. (2022) Malandrakis & Drakos (2025)
	Non-Performing loans to total assets (<i>NPL/TA</i>)	Non-performing loans divided by total assets, expressed as a percentage and used in logarithmic form to reduce skewness. Captures asset quality; higher values signal deteriorating loan portfolios.	Orbis	Birindelli et al. (2022) Malandrakis & Drakos (2025) Reghezza et al. (2022) Demetriades & Politsidis (2025)
	Cost-to-income (CIR)	Operating expenses divided by operating income, expressed as a percentage. Proxies managerial efficiency; lower values indicate more efficient cost management.	Orbis	Chiaramonte et al. (2022) Baselga-Pascual et al. (2015)
	Return on Equity (ROE)	Net income available to common shareholders. Estimated by subtracting preferred dividends from net income and dividing the results by the average common equity between the previous year (<i>t-1</i>) and the current year (<i>t</i>). Measures profitability and the	LSEG Workspace	Demetriades & Politsidis (2025) Ebrahim et al. (2025) Palvia et al. (2015)

		effectiveness of management in generating returns from the common equity base.		
	Loan to deposits	Total customer loans divided by total customer deposits. Values above 1 indicate that a bank funds part of its loan book from non-deposit sources; commonly used as a proxy for funding liquidity risk.	LSEG Workspace Authors	
	Bank size (log(Total Assets))	Natural logarithm of total assets in USD. Controls for economies of scale, regulatory treatment (too-big-to-fail effects), and differences in business model complexity.	LSEG Workspace	Reghezza et al. (2022) Jung et al. (2025) Degryse et al. (2023) Demetriades & Politsidis (2025) Palvia et al. (2015 & 2020) Ebrahim et al. (2025)
	GDP growth rate	The average annual growth rate of a country's Gross Domestic Product (GDP).	World Bank	Chiaramonte et al. (2022)