Systemic and climate risks in the banking sector: evidences from syndicated lending and net-zero commitments

Article

Thesis

Sina, A. (2026) Systemic and climate risks in the banking sector: evidences from syndicated lending and net-zero commitments. doi: 10.48683/1926.00128512 (Unpublished) Available at https://centaur.reading.ac.uk/128512/

Identification Number/DOI: 10.48683/1926.00128512
<https://doi.org/10.48683/1926.00128512>

Systemic and Climate Risks in the Banking Sector:

Evidences from Syndicated Lending and Net-Zero Commitments

Thesis submitted in partial fulfilment of the requirements

for the degree of Doctor of Philosophy

HENLEY BUSINESS SCHOOL

THE UNIVERSITY OF READING

ICMA Centre

Ana Sina

September 2025

Declaration

I confirm that this is my own work and the use of all material from other sources has been properly and fully acknowledged.

Ana Sina

Declaration of Generative AI and AI-assisted technologies in the writing process

During the preparation of this work the author used ChatGPT in order to improve the grammar and flow of the text. After using this tool, the authors reviewed and edited the text as needed and take full responsibility for the content of this work.

Ana Sina

Abstract

This thesis investigates systemic risk and climate risk as distinct yet interconnected sources of financial vulnerability in the banking sector. ***Chapter 1*** outlines the thesis contributions and overall structure. ***Chapter 2*** reviews the relevant literature. ***Chapter 3*** examines syndicated leveraged and covenant-lite loans as potential channels of systemic risk. We show that while these loans are not inherently systemic, banks with large exposures become more vulnerable during recessions, and pipeline risk can rise when market conditions hinder loan sales. Furthermore, although the banking network has historically become less interconnected due to the participation of smaller institutions, the centrality of large banks amplifies the risk of contagion. These findings suggest that regulators should closely monitor the exposure of highly central banks to such loans.

Chapter 4 examines how climate factors influence systemic stability in the U.S. syndicated loan market. Using climate risk measures, green lending orientation, and regional indicators, we identify four key drivers of systemic risk: banks' environmental stance, extreme events in the South, precipitation anomalies in the East, and changes in U.S. climate policy. While exposure to climate-sensitive regions increases vulnerability, green lending appears to enhance stability. These findings underscore the importance of climate policies that reduce uncertainty and support sustainable lending.

Chapter 5 uses data on Net-Zero Banking Alliance (NZBA) members to show that banks making progress toward decarbonization targets exhibit lower climate risk, as measured by CRISK. However, between late 2024 and early 2025, several large North American and Japanese banks withdrew from the NZBA. Evidence points to U.S. electoral outcomes, rather than financial or institutional factors, as the main driver of these exits. This highlights the vulnerability of climate coalitions to political shifts, raises doubts about the feasibility of the 2050 net-zero goal, and emphasizes the need to strengthen the Alliance's resilience across different political contexts.

Acknowledgements

This letter is long, but after seven years of work and three moves across different countries, I've finally reached the end of this journey thanks to the support of many people.

To my examiners, you have accompanied me to the end of a long and intense journey, making my viva a truly enriching experience. I am sincerely grateful for the thoughtful feedback you shared, which has greatly helped to improve these chapters.

To my supervisors: your constant support and understanding through all the ups and downs of this PhD made this thesis possible.

Simone, you taught me to be resilient, to plan realistically, and to keep adapting, always positively. You showed me how to stay focused on my goals and not get sidetracked. Every time I followed your advice, things got better, both in practical terms and in how I felt. Thank you, I hope I always remember your lessons.

Alfonso, your calm and positive attitude helped me stay grounded. Your insights, especially in the more technical parts, often made me pause and think, "I hadn't seen it that way before." You were never intrusive throughout this journey, yet always present at just the right moments, when it truly mattered. Thank you so much.

Monica, I'm truly grateful. You selected me for the CFA Challenge and the Double Degree program, and you replied to my call when after years in industry, I realized it was time to pursue a PhD. Your support has truly changed my life. During my two maternity leaves, I feared I might not finish, but you understood what I was going through and never doubted that I would. In fact, you even found ways to support me during those times.

To the PhD community at the ICMA Centre — Corina, Daniele, Dina, Filippo, Francesco, Loua, Ludovico, Mirco, Moustafa, Samuele, Victoria, and many others — thank you for the coffee breaks, dinners, exchange of ideas, and informal seminars we shared. A special thanks to Loua: I found a true friend in this journey. Sharing our experiences of motherhood and supporting each other made a real difference.

To the ICMA Centre professors' community and especially to—Michael Clements, Konstantina Kappou, Emese Lazar, Brian Scott-Quinn, Lisa Schopol, and Ivan Sangiorgi—thank you for your valuable and constructive feedback throughout this journey. Your comments and questions helped me sharpen my ideas, improve my research, and grow as a scholar.

To the many people I've met at conferences, seminars, workshops, and summer schools—the many revisions these papers have undergone are the result of fruitful idea exchanges and constructive feedback, for which I am truly grateful.

Massimo, even though my contribution was only marginal, working with you remotely as a TA gave me short-term goals that helped me stay connected to academic life—it made a real difference. Thank you for your patience, especially during the final period when balancing everything became challenging. Your understanding really meant a lot.

To Nazarbayev University: thank you for welcoming me and making me feel part of this environment.

To Leanne and Karen, your positive energy makes the ICMA a better place, and our morning chats always helped me start the day with a smile.

Daniel and Stephanie, Daniele and Chivon, Stephen and Marianne, Giudit and Ricky, Alonso and Claudia—you made me feel part of a family I remember with affection. Thank you also to the Rome and Veneto communities, especially Chiara and Stefano. Manuela, Massimo, and your children—your hospitality really moved me. Beatrice, Annalisa, Maria, and Miriam—your help meant so much.

Ali, you're the best landlord I could have hoped for— authentic, energetic, and full of life.

Dinara, thank you for the kind and caring way you help me every day. And to the many people I've met in Kazakhstan—Assel, Carolina, Cassia and Dimitri, Lucie, Mandana, Noua, Zohra, and others—thank you for your support, each in your own way. Carolina, I'm truly grateful for your suggestion—so simple yet powerful: "Set yourself a daily word count target."

Alex, Ambra, Ana, Eni, Federica, Giulia, Greta, Isabella, Luca, Massimiliano, Michela, Serenella, Sonia, and my friends from Stigliano and Rome — no matter how often I move, seeing you always feels like no time has passed. You have left a lasting mark on my journey.

To my in-laws, Domenico and Rosanna; to Chiara and Massimiliano, Valerio, Uncle Franco and Cinzia; and especially to Grandma Loreta—being part of my own family is natural, but being welcomed into a new one is something special. Thank you for that.

To my aunts and uncles, Merita, Fatmir, Ferdinando, Juliana, all my cousins, and the grandparents I carry in my heart — your love is the foundation of our big family.

Francesco, it was love at first sight the moment I saw you at the office—I immediately felt at home. You are the most wonderful gift this PhD has given me, and I'm deeply grateful that today, you are my home.

Sofia and Giuseppe, I've realized it takes more time to write academic papers than to bring two amazing little humans like you into the world—what a miracle! You are my greatest joy.

To my own family—Mom, Dad, my brother, and Grandma—you've always been there for me, with all the emotions that come with it. You are the best family I could ask for. This thesis is dedicated to you.

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List of acronyms

BCBS	Basel Committee on Banking Supervision
CCSP	Climate Change Science Program
CEO	Chief Executive Officer
CH	Crimson Hexagon
CLOs	Collateralized Loan Obligations
CRISK	Climate Risk Expected Capital Shortfall
G-SIBs	Globally Systemically Important Banks
GFC	Global Financial Crisis
LBO	Leveraged buyout
LRMES	Long-Run Marginal Expected Shortfall
M&A	Merger and acquisition
NBER	National Bureau of Economic Research
NCEI	National Centers for Environmental Information
NDC	Nationally determined contributions
NGFS	Network for Greening the Financial System
NWS	National Weather Service
NZBA	Net-Zero Banking Alliance
PDSI	Palmer Drought Severity Index
PRB	Principles for Responsible Banking
PRI	Principles for Responsible Investment
ROA	Return on assets
SDGs	Sustainable Development Goals
SFDR	Sustainable Finance Disclosure Regulation
SIFI	Systemically important financial institution
TCFD	Task Force on Climate-related Financial Disclosures
UN	United Nations
UNEP FI	United Nations Environment Programme Finance Initiative
WSJ	Wall Street Journal

1. Introduction

1.1. General background and motivation for the Thesis

Although the syndicated loan market experienced a severe contraction and declined by approximately 40% during the Global Financial Crisis (GFC) (Ivashina and Scharfstein, 2010), it has since recovered and now plays a central role in corporate finance. In particular, the U.S. syndicated loan market has emerged as the largest globally and currently represents the second most important source of external funding for large non-financial corporations, surpassed only by the corporate bond market (Saharti et al., 2024). Within this broader segment of the market, two categories have expanded markedly over the past twenty years: leveraged loans, typically granted to borrowers with high debt levels or below-investment-grade ratings, and covenant-lite loans, which include fewer contractual safeguards for lenders. Both types have seen their market share more than triple, attracting heightened attention from regulators and the press, particularly in the U.S. and Europe. The growth of covenant-lite lending, in particular, appears to be largely driven by the increasing role of institutional investors outside the traditional banking sector, such as mutual funds and structured investment vehicles, whose preference for reduced lender control tends to shape the structure of loan agreements (Becker and Ivashina, 2016). This evolution was also influenced, in part, by the introduction of the 2013 Leveraged Lending Guidance. Although the regulation initially led to a decline in the volume of leveraged loans and a reduction in overall risk, as indicated by lower participation from nonbank syndicate members, it also produced several unintended effects. These include a weakening of covenant protections, narrower loan spreads at origination, and a shift of higher-risk lending toward nonbank financial institutions operating outside the scope of banking regulation (Schenck and Shi, 2022).

Policymakers have increasingly voiced concerns about the rapid expansion of the leveraged loan market. Former Federal Reserve Chair Janet Yellen, for example, warned that lending standards in this segment have weakened, raising potential risks for financial stability. As detailed in the technical report by Lee et al. (2019), the fast growth of this market has been driven by a shift in banks' operational approach. Rather than holding loans on their balance sheets, banks now commonly structure them for sale shortly after origination, primarily to outside investors such as Collateralized Loan Obligations (CLOs) and mutual funds. This change has increased banks' vulnerability to both credit losses and pipeline risk, particularly when investor demand is insufficient. In these scenarios, banks end up retaining a larger share of the loans than intended, often including the riskiest exposures. Under normal conditions, banks are able to sell off most of these high-risk, non-investment-grade loans within a few weeks of origination. However, during periods of market stress, such as during the global financial crisis, this process could slow significantly. As a result, banks may be forced to hold onto risky assets for longer than expected, increasing their exposure at times when financial conditions are already strained. Despite this heightened regulatory attention, the academic literature has yet to fully investigate the systemic risk implications associated with the rise of leveraged and covenant-lite syndicated loans. In particular, it remains unclear to what extent these instruments might exacerbate financial shocks through the networked nature of syndicated lending. This issue is especially relevant given the structural characteristics of the market: syndicated loans are typically extended by a consortium of financial institutions to a single borrower, thereby creating a web of interdependencies across banks. These interconnections are widely recognised as potential channels for the propagation of systemic risk (Cai et al., 2018). In this thesis, we investigate potential channels of systemic risk propagation by analysing the syndicated loan network and introducing a novel measure, SN_RISK, which captures banks' exposure to the U.S. syndication market.

Both ***Chapter 3*** and ***Chapter 4*** focus on systemic risk as the main variable of interest. Although the academic literature proposes various definitions and measurement approaches to systemic risk, no unified or widely accepted standard emerges. For instance, a comprehensive review by Ellis et al. (2022) identified 60 distinct systemic risk measures across 4,859 academic abstracts, highlighting the field's conceptual diversity. Prominent definitions include the simultaneous failure of a significant portion of the financial sector (Acharya et al., 2011; De Bandt and Hartmann, 2000), disruptions to the normal functioning of financial markets (Adrian and Brunnermeier, 2008), and the co-movement of defaults across financial institutions (Billio et al., 2012). In this study, we adopt the systemic risk metric developed by Acharya et al. (2017), which estimates the capital shortfall that financial institutions would face in a systemic crisis. This measure is particularly well-suited to our analysis, as it enables an empirical assessment of whether banks' involvement in syndicated leveraged and covenant-lite loans increases their vulnerability to systemic stress. By focusing on capital adequacy under adverse conditions, this approach captures not only the likelihood of institutional distress but also its potential impact on the broader system. It thus offers a relevant and tractable tool to examine how evolving loan structures may propagate systemic risk through interconnected financial networks.

While much of the existing research on syndicated loans has emphasised credit risk and financial performance, relatively little attention has been paid to the role of these loans in facilitating, or potentially hindering, the transition to sustainable finance (Saharti et al., 2024). As emphasised by Bolton et al. (2020), there is a growing need to deepen our understanding of how climate-related risks intersect with financial stability. In response, this thesis expands the analysis of systemic risk by incorporating environmental dimensions into the framework. Building on the control variables introduced in ***Chapter 3***, ***Chapter 4*** incorporates several climate risk indicators to examine which of them account for cross-variations in banks' systemic risk. This reflects a broader shift in the literature, which increasingly recognises that climate risks are complex, heterogeneous, and unlikely to be fully captured by a single proxy, a limitation that may constrain research in this area. To this end, we incorporate a comprehensive set of climate-based metrics. First, we introduce a proxy for banks' relative engagement in environmentally sustainable lending, to reflect their alignment with green finance objectives. Second, we estimate banks' exposure to physical climate hazards across U.S. regions, based on physical climate data weighted by the geographic distribution of their loan portfolios. Third, we add literature-based indicators that capture media attention, transition risk, and policy developments. Taken together, these dimensions provide a more nuanced perspective on the channels through which climate risks may amplify systemic vulnerabilities. By combining firm-level behaviour with macro-level exposures, this framework aims to identify the climate risk factors that drive financial instability. It can support the design of climate risk assessments and stress tests that consider multiple sources of systemic risk, including banks' loan exposures, physical risks in vulnerable regions, and policy uncertainty. This multidimensional view offers a more complete and realistic evaluation of the relationship between climate and systemic risk.

The thesis concludes by addressing a recent and pressing concern: the growing vulnerability of climate banking initiatives in the context of evolving political conditions. Following the most recent U.S. elections, several large banks headquartered in North America and Japan publicly announced their departure from the Net-Zero Banking Alliance (NZBA). These decisions seem to reflect a strategic response to a political environment that is increasingly characterised by reduced climate ambition, weakening international cooperation, and a resurgence of policy support for fossil fuel industries. These developments have raised important questions about the long-term credibility and resilience of voluntary climate commitments within the financial sector. ***Chapter 5*** presents an empirical analysis of how shifts in political leadership, particularly in the United States, can undermine banks' climate pledges, even when made under robust governance frameworks such as the NZBA. Our primary metric is the climate risk measure developed by Jung et al. (2025), which captures banks' exposure to potential financial losses from stranded assets. These are assets that may lose their value or become obsolete due to the introduction of new climate regulations aimed at accelerating the transition to clean energy. We then incorporate variables capturing NZBA commitments, political outcomes in the U.S., and banks' financial characteristics. The NZBA offers an ideal setting for this analysis because of its stringent accountability requirements: signatory banks must set tangible decarbonization targets and report their progress. This high degree of transparency enables an assessment of how shifts in political leadership affect the credibility and implementation of banks' climate strategies.

1.1 Intended Contributions

Each chapter of this thesis offers a distinct empirical contribution to the literature on the impact of systemic and climate-related risks on banking system stability, informed by ongoing regulatory developments and academic research.

Chapter 3 contributes to the literature by shedding light on a relatively understudied and increasingly important segment of the syndicated loan market: leveraged and covenant-lite loans. These instruments have attracted growing regulatory attention, largely due to their elevated risk profiles and their potential to amplify financial instability during economic downturns. Accordingly, this study's main contribution lies in creating a new syndicated portfolio risk measure, which provides empirical insight into a matter of ongoing debate. This metric is specifically designed to quantify banks' exposures to leveraged and covenant-lite loans and offers a more precise understanding of how such exposures may contribute to systemic vulnerabilities. By capturing risk concentration in this segment, the measure provides valuable insights for both researchers and policymakers monitoring financial stability. In addition, it serves as a practical tool for identifying institutions that may be more vulnerable in periods of market stress. This measure is shown to be robustly associated with cross-sectional variations in banks' systemic risk, holding across a variety of alternative specifications and robustness checks. We provide empirical evidence that this market segment can act as a significant amplifier of systemic risk, particularly during economic downturns. To our knowledge, this is the first empirical study to apply the methodology developed by Blickle et al. (2020) to estimate banks' retained exposures to syndicated leveraged and cov-lite loans. This approach incorporates post-origination retention data, enabling us to capture exposures not only for lead arrangers but also for non-lead banks, a group that has often been overlooked due to data limitations. This broader coverage enhances our understanding of the true distribution of risk within the syndicated loan market. By including non-lead participants, the analysis contributes to understanding how risk is shared across a wider range of institutions. It also sheds light on the extent to which systemic vulnerabilities may be underestimated when only lead bank exposures are considered. Importantly, our study extends beyond the traditional focus on lead arranger relationships (e.g., Cai et al., 2018; De Novellis et al., 2024) by examining the full interbank network of syndicated lending. We show that increasing participation by more peripheral banks leads to a higher level of interconnection across the system, while simultaneously reducing the average centrality of major banks. This structural shift in the network has important implications for how credit risk propagates across institutions, especially in times of financial distress. It indicates that systemic risk can come not just from the most connected banks, but from how lending relationships are structured across the entire network.

The second study, presented in ***Chapter 4***, examines the intersection of systemic and climate risk by developing a novel framework that combines banks' environmental lending behaviour, their geographic exposure to physical climate hazards, and literature-based indicators capturing multiple climate-related dimensions. Whereas previous studies often rely on a single climate indicator, we adopt a broader and more granular approach. Specifically, we combine eight indicators drawn from the existing literature with 25 new measures constructed using climate variables, when possible, adjusted by the distribution of banks' syndicated loan portfolios. As part of this framework, we create bank-level indicators of environmental responsibility by evaluating the climate profiles of syndicated loan borrowers. This provides a behavioural proxy for how environmentally conscious each bank's credit allocation strategy is.

Simultaneously, we assess banks' exposure to physical climate risk by mapping their lending activity across U.S. regions historically affected by extreme weather events and long-term environmental changes. This study offers three main contributions. First, we find that banks with stronger environmental lending practices tend to exhibit lower levels of systemic risk, indicating that financial markets reward more sustainable credit allocation. This suggests that institutions actively supporting the green transition are perceived as more resilient and better equipped to manage long-term risks. The result underscores a growing market recognition of the financial value embedded in environmentally responsible lending strategies. Second, the analysis confirms that banks with greater exposure to physical climate risks, such as floods, hurricanes, and long-term temperature increases, tend to exhibit higher levels of systemic vulnerability. Although this relationship has been acknowledged in previous studies, our regionally focused approach offers a more detailed perspective. In particular, we find that the impact of climate events on systemic risk is not uniform across the United States. It varies according to the geographic distribution of their lending activities and the specific type of climate hazard. This finding underscores the importance of incorporating both spatial and event-specific factors when assessing the financial implications of physical climate risks. Lastly, the study finds that the introduction of new climate policies tends to raise banks' systemic risk in the short term. This outcome suggests that markets perceive regulatory transitions as a source of uncertainty and potential disruption for financial institutions, particularly those with significant exposure to high-emission sectors. The initial increase in risk may reflect the challenges banks face in adjusting their portfolios to meet stricter environmental standards, such as the risk of stranded assets or abrupt revaluations of carbon-intensive investments. Over time, however, such policies are likely to encourage more sustainable credit allocation, which could enhance long-term financial stability. These results highlight the importance of policy design and clarity, as well as the need for gradual implementation and coordination to minimize transitional shocks to the banking system. Furthermore, they emphasize that short-term risks from climate regulation should not amplify systemic risk but rather guide banks and regulators toward more adaptive and resilient strategies.

The third study examines what drives banks to join the Net-Zero Banking Alliance (NZBA), a voluntary global initiative that aims to align financial institutions with the goal of achieving net-zero greenhouse gas emissions by 2050. To our knowledge, this is the first empirical investigation into how NZBA membership influences banks' exposure to climate-related financial risks, using the recently introduced metric by Jung et al. (2025). Beyond assessing the impact of participation, the study applies a political economy perspective to explore the factors leading some banks to exit the alliance. This research contributes to the growing literature on the effectiveness of voluntary climate commitments in the financial sector. Our findings indicate that banks actively implementing NZBA targets experience measurable reductions in climate risk, offering early evidence that such initiatives can enhance financial resilience. Furthermore, our analysis shows that banks' decisions to participate in the NZBA are significantly shaped by their institutional and political environments. External pressures—such as regulatory expectations, public scrutiny, and policy signals—can either encourage or discourage voluntary climate engagement. These findings highlight the importance of national regulatory systems that are aligned with global climate initiatives to support their credibility, promote broader participation, and ensure lasting impact. Yet, our study also uncovers a concerning trend: politically motivated withdrawals from the NZBA, particularly in contexts where climate policy is becoming increasingly polarised. Notably, several major financial institutions based in North America and Japan—including Citigroup, Bank of America, Morgan Stanley, and MUFG—have recently exited the alliance. Our empirical analysis indicates that these exits were not motivated by financial considerations. Rather, they represent a response to changing political dynamics, particularly after the U.S. elections, which marked a broader retreat from ambitious climate regulation.

Our results highlight the opportunity for banks to make their climate commitments more resilient to political cycles. This politically driven disengagement highlights a crucial vulnerability of voluntary climate commitments: their dependence on stable political context. In environments marked by political uncertainty or anti-climate sentiment, banks may shift their priorities. As such, the credibility of net-zero pledges remains fragile in the absence of robust frameworks. To address this risk, stronger institutional mechanisms and international coordination are needed to ensure the effectiveness of climate initiatives despite political cycles and to keep financial actors committed to the low-carbon transition. For example, embedding climate targets into enforceable regulatory requirements could reduce the scope for politically motivated withdrawal, while harmonizing disclosure standards could enhance transparency and public accountability. Over time, such measures could foster a more resilient and depoliticized foundation for global climate finance.

1.2 Outline of the thesis

The main body of the thesis is structured across ***Chapters 3***, ***4***, and ***5***. Each chapter presents an independent empirical investigation into a specific channel through which systemic and climate-related risks affect banking system stability. Although each study stands on its own, ***Chapters 3*** and ***4*** are closely connected, with the latter building on the main results of ***Chapter 3*** by adding climate risk to the factors explaining banks' systemic risk. ***Chapter 5***, by contrast, introduces a more institutional and policy-oriented study.

In more detail, ***Chapter 3*** focuses on systemic risk in the syndicated loan market, with particular attention to the role of banks' exposures to leveraged and covenant-lite loans. The chapter investigates how variations in these exposures help explain cross-sectional differences in systemic risk among banks. Section 3.2 lays out the methodological framework employed in the study. It introduces a novel measure of syndicated portfolio risk tailored to capture the riskiness of banks' loan books, as well as various network analysis indicators, such as centrality and interconnectedness, which serve as proxies for banks' systemic relevance within the market. The empirical analysis relies on panel regression models that incorporate these variables, along with a set of bank-level controls. Section 3.3 describes the data used in the study. Syndicated loan-level data and information on bank participation are sourced from DealScan, while bank-level systemic risk metrics (SRISK) are obtained from the V-Lab at NYU Stern. These two datasets are merged to construct a monthly panel covering 96 banks—including both global systemically important institutions and smaller banks—for a total of 11,154 observations. This integrated dataset allows for an in-depth analysis of how specific portfolio characteristics and structural positions within the syndicated loan network influence a bank's contribution to systemic risk.

Chapter 4 builds on the framework developed in ***Chapter 3*** to analyze lenders' syndicated loan portfolios and assess how environmental lending and exposure to physical and regulatory climate risks affect banking system stability. The chapter retains several methodological elements from the previous analysis, including the use of panel regression models including the same control variables, to ensure comparability across chapters. Section 4.2 outlines the methodological framework, while Section 4.3 describes the main data. The empirical analysis is conducted on a panel of 61 banks over 4,334 monthly observations. The results show that stronger environmental lending profiles are associated with lower systemic risk, whereas exposure to both short-term and extreme physical climate risks increases systemic vulnerability. Importantly, the study finds that banks' systemic risk is highly sensitive to the introduction of new climate-related regulations, which underscores regulatory uncertainty as a central driver of climate-related financial risk.

Remaining within the banking sector, ***Chapter 5*** shifts the focus from market exposures to institutional engagement with global climate initiatives. Specifically, it examines banks' participation in the NZBA, a voluntary commitment to align lending portfolios with net-zero emissions by 2050. The chapter examines both the climate risk implications of joining the NZBA and the political factors that drive banks' decisions to withdraw from the alliance. Section 5.3 presents the methodological approach, which relies primarily on the climate risk measure developed by Jung et al. (2025). This metric estimates potential losses from stranded assets arising from policy shifts toward greener energy. Two empirical models are employed. The first is a bank-level panel regression model designed to test whether NZBA membership is associated with reductions in climate risk. This model includes 85 banks and covers 19,869 monthly observations. The second model is a logit regression that estimates the likelihood of a bank exiting the NZBA, based on a set of political, institutional, and financial variables. Since the NZBA was launched in 2021, the sample used for the logit model includes 4,074 monthly observations for the same group of banks. The main data sources include the Principles for Responsible Investment (PRI) website, which provides information on NZBA membership, and NYU V-Lab, from which the climate risk variable is extracted. The chapter concludes by offering several suggestions for future research, particularly in light of the novelty of the dataset and the ongoing developments in banks' climate strategies. The analysis emphasizes the evolving role of financial institutions in addressing climate risk and the importance of understanding the dynamic interaction between policy commitments, market expectations, and institutional behaviour in the pursuit of net-zero targets.

2. Literature Review

This chapter presents a comprehensive review of studies related to the topics addressed in this thesis. The first section explores research on syndicated loans, with a focus on studies that investigate this market in relation to systemic risk. The second section reviews the literature on climate change, with specific attention to works that examine the link between climate factors and systemic risk, which forms a central focus of our analysis. The final section examines the literature on political risk in financial markets and then considers studies that analyse the relationship between climate and political risk.

2.1. Evolution of the syndicated loan market and its link to systemic risk

Since both ***Chapters 3*** and ***4*** focus on the syndicated loan market and use it as the primary setting to examine its connection to systemic risk, this section explains the reasons behind the growing interest in this market. It then reviews the main findings in the literature regarding the forms of systemic risk that syndicated loans can generate within the financial system. Evidence of syndicated loan activity can be traced back to the 1960s within the broader international banking market (Rhodes, 2000). Systematic academic research on the syndicated loan market began to develop more substantially only in the past two decades (for notable contributions, see Dennis and Mullineaux, 2000; Armstrong, 2003; Altunbaş et al., 2006; Sufi, 2007; Gatev and Strahan, 2009; Ferreira and Matos, 2012). Comprehensive literature reviews have been provided by Gilchrist et al. (2021), Luma (2022), Khandelwal (2021), and Saharti et al. (2024). Over time, academic interest in syndicated lending expanded considerably, with many studies seeking to identify the structural and macroeconomic forces driving its rapid growth. The literature (Armstrong, 2003; Altunbaş et al., 2006; Le et al., 2008) identifies several pivotal developments: the emergence of the Eurodollar market in the 1960s; balance-of-payments pressures in non-oil-exporting emerging economies during the 1970s; the Latin American debt crises and the U.S. merger wave of the 1980s; and, in the 1990s, an increasingly competitive financial landscape alongside the rise of the secondary loan market. The expansion of the cross-border interbank market further amplified this growth, as the resulting liquidity and enhanced risk-sharing mechanisms in the secondary market fostered greater activity in the primary syndicated loan market. During this period, the market was dominated by some of the world’s largest and most influential financial institutions, while borrowers were mostly major corporations with significant financing requirements, often representing central pillars of national production and economic growth. Early studies focused predominantly on the U.S. market, which then, as now, remains the largest globally in terms of loan issuance volumes.

The global financial crisis represents a pivotal shock to the syndicated loan market, drawing significant attention due to its immediate and pronounced impact on issuance volumes (De Haas and Van Horen, 2009; Gasbarro et al., 2017). In 2008, total loan issuance declined sharply, driven largely by mounting pressures on international banks’ balance sheets (Chui et al., 2010). Kapan and Minoiu (2013) provide evidence that institutions with stronger balance sheets, measured according to prudential metrics later incorporated into Basel III, were better positioned to maintain their intermediation function, thereby cushioning the contraction in credit supply relative to weaker banks. Alexandre et al. (2014) further show that the crisis induced a tightening of lending standards; however, borrowers with established relationships with lead arrangers benefited from comparatively lower loan spreads and longer maturities. Giannetti and Laeven (2012) also find that, amid heightened risk aversion, banks shifted their activity toward domestic markets, reflecting altered risk perceptions and return expectations during a period of severe financial stress.

Over time, the purposes for which syndicated loans are extended have also changed. In the 1980s, they served primarily as a major source of financing for mergers and acquisitions as well as leveraged buyout activities. In the 1990s, their use shifted, with 49.5% of loan volume directed toward general corporate purposes and 33.5% toward debt repayment (Dennis and Mullineaux, 2000). In more recent years, while general corporate purposes have remained one of the leading uses of syndicated loans, two other purposes have become prominent: capital expenditure and working capital. For instance, based on our calculation, in 2022, general corporate purposes accounted for 33% of loan volume, capital expenditure for 28%, and working capital for 19%. One of the most significant transformations in the syndicated loan market over time has been the evolving nature of lender–borrower relationships. As Bavaria (2002) observes, the growing reliance on agency credit ratings in the late 1990s and early 2000s fundamentally reshaped the U.S. syndicated loan market. What had previously functioned largely through long-standing banking relationships gradually shifted toward a more marketoriented framework, marked by higher efficiency and increasingly influenced by investor participation. This transformation extended beyond the relational dimension to the very composition of participating institutions. Alongside large global banks, the market now features a greater presence of smaller banks and non-bank financial institutions, including hedge funds and insurance companies. As illustrated by the network analysis in ***Chapter 3***, the market's structure has become far more complex than in the past, with a denser web of connections among participants and the entry of more peripheral financial actors, further diversifying its configuration. This growing complexity has led scholars to analyse the syndicated loan market as a financial network, offering insights into how institutions interact, especially the connections between systemically important banks and smaller entities, as well as the overall patterns of market relationships (Godlewski et al., 2012; Hale et al., 2016; Gupta et al. 2017; Inekwe, 2021; Sina et al., 2025).

While the U.S. syndicated loan market remains the most extensively studied, largely because of its superior data availability and quality, scholarly attention has increasingly broadened beyond it. Over the past decade, a growing body of research, in some cases with a particular focus on economic downturns, has extended analysis to European countries (Berg et al., 2021; Steffen and Wahrenburg, 2008; Saunders and Steffen, 2011; Drago and Gallo, 2020; Howcroft et al., 2014) and to emerging markets (Gadanecz, 2004; Nini, 2004; Levine, 2005; Altunbaş et al., 2006; Godlewski and Weill, 2008; Takáts, 2010; Caporale et al., 2018).

Numerous other studies explore the syndicated loan market from diverse perspectives. Among the most common approaches, a central focus is often placed on loan pricing, with research examining how factors such as borrower characteristics, market conditions, and institutional structures influence spreads and contract terms (Gupta et al., 2008; Hasan et al., 2021; Pinto et al., 2024; Zhang et al., 2024; Saunders et al., 2025). In other cases, the analysis centers on credit ratings, investigating their role in shaping market access, pricing, and risk assessment, as well as their interaction with broader financial stability concerns (Yi and Mullineaux, 2006; Aramonte, Lee, and Stebunovs, 2022; Balasubramanyan et al., 2019). Further research narrows the focus to specific categories of loans, such as non-performing loans (Shiralashetti and Poojari, 2016; Steffen and Wahrenburg, 2008) and, in some cases, leveraged or covenant-lite loans (Barnish et al., 1997; Cathcart et al., 2024; Steffen, 2024), which are of particular interest given their distinct risk profiles and potential implications for market stability.

In ***Chapter 3***, our analysis focuses on the market for leveraged and covenant-lite syndicated loans, examining its relationship with banks' systemic risk. While other studies have explored the connection between syndicated loans and systemic risk, their approaches differ from ours in both scope and methodology, which are described in detail in ***Chapter 3***. Cai et al. (2018) introduce a novel measure of bank interconnectedness based on the distance between their portfolios in terms of sectoral and regional allocations. They find that greater portfolio overlap is associated with higher systemic risk, particularly during periods of economic recession. Gong et al. (2014) show that loan pricing incorporates valuable information on systemic risk, finding that higher levels of such risk are associated with lower loan spreads.

Increasing attention is being paid to the relationship between systemic risk and syndicated loan exposure in markets outside the U.S., driven by the growing issuance volumes in other regions. For example, Drapeau and Champagne (2015) find that the impact of diversification in the Canadian syndicated loan market on systemic risk varies depending on the systemic risk measure employed in the analysis. In the Japanese syndicated loan market, Kanno (2022) applies network analysis and shows that the most influential nodes are the largest Japanese banks, major regional banks, and Japanese Real Estate Investment Trusts (J-REITs). These patterns mirror those observed in the U.S. market, suggesting that market structure and institutional concentration can create similar systemic vulnerabilities across different jurisdictions. Similarly, Cao et al. (2022) identify the "too-connected-to-fail" characteristic as intrinsic to the syndicated loan network within the Chinese financial system. In other words, banks with greater network relevance tend to be more systemically important, regardless of their size in terms of total assets. Moreover, by extending the analysis to the closely linked markets of Japan and Taiwan, they uncover a tangible risk of financial shock transmission through common holding exposures and high network centrality. This points to the possibility that regional interconnectedness can accelerate the cross-border spread of financial distress, making local disruptions capable of triggering wider systemic episodes.

2.2. Relationship between climate risk and systemic risk

Chapter 4 investigates the relationship between climate risk and systemic risk. Aglietta and Espagne (2016) argue that the connection between the two is so strong that they introduce the concept of “climate systemic risk” to capture this inherent overlap. Our study departs from previous ones in two important ways. First, we use the actual portfolio exposures of banks, allowing for a more accurate representation of their geographical footprint within the United States, rather than relying on aggregate market or regional averages. Second, we incorporate a wide and diversified set of climate risk indicators, each selected to detect different types of climate-related effects that could potentially influence systemic stability. After constructing this framework, we examine which of the several measures used in the analysis hold statistical significance.

The academic and policy interest in climate risk has expanded significantly in recent years, and research on its connection to systemic risk has grown accordingly. We can distinguish two broad dimensions of climate risk: physical risk and transition risk (Monasterolo, 2020). Understanding both is essential, as they transmit shocks through distinct channels and can affect the resilience of the financial system in different ways. A substantial body of work focuses on transition risk. Gros et al. (2016) suggest that an abrupt shift toward lower-carbon energy production could heighten systemic risk through three main mechanisms. First, energy costs might rise if cleaner energy sources are not yet available in adequate supply, which would slow GDP growth by pushing up production costs and lowering competitiveness. Second, a sudden loss in the value of carbon-intensive assets could weaken public finances by raising debt burdens and eroding fiscal capacity. Third, such a transition could occur at the same time as more frequent and severe extreme weather events, increasing liabilities for insurers and reinsurers and thereby placing further strain on the financial system.

Ojea Ferreiro et al. (2022) model three alternative future scenarios, named “ordered transition,” “disorderly transition,” and “no transition,” to estimate how the value of financial assets might evolve under each scenario. Their results show that cost impacts are highly sector-specific: a disorderly transition generates the steepest losses for banks, financial services suffer less, and real estate firms are relatively affected under disorderly conditions but face their most severe losses when no transition occurs at all. These sectoral differences underline how different transition pathways can redistribute systemic vulnerabilities across the economy. Alessi et al. (2024) apply a climate stress-testing framework to European banks under a baseline scenario and conclude that, on average, capital requirements would need to increase by about 0.9% of risk-weighted assets to account for transition risks. This figure illustrates that even under moderate assumptions, transition risks can translate into tangible and measurable capital needs. Reviewing the literature, Oguntuase and Ajibare (2024) identify 89 relevant publications, mostly published between 2021 and 2023, and find that while methodologies vary widely, the prevailing consensus is that transition risk has the capacity to amplify systemic vulnerabilities.

Physical risk constitutes another potential transmission channel for systemic fragility. Much of the related literature concentrates on the economic consequences of extreme weather events. Conlon et al. (2024), weighting extreme climate data by state-level exposure, find that physical risks can intensify systemic risk within the banking sector. Building on these findings, we employ a wider set of physical risk indicators, capturing both short-term and medium-to-long-term climate factors. We then integrate these with measures of banks' environmentally friendly attitudes. Finally, we draw on several established metrics from the literature to provide a more comprehensive view of climate-related threats to stability within the syndicated loan market. Extending the scope beyond banks, Curcio et al. (2023) show that certain extreme events also raise systemic risk for insurers. Interestingly, their results suggest that increases in green index values, tracking the MSCI USA Investable Market Index and the NASDAQ OMX Green Economy US Index, can partly offset these negative effects for both banks and insurers.

Some studies consider both types of risk together in order to assess whether one or both are driving increases in systemic fragility. Jourde and Moreau (2022), focusing on European banks, find that transition-related risks can have a clear systemic impact, yet also show that adopting long-term climate strategies and improving disclosure practices can dampen this effect. Their analysis indicates that physical risks, while present, are less influential in triggering systemic contagion. In the Chinese financial system, Tian and Li (2025) examine indices designed to capture physical and transition risk, finding that transition risk significantly raises systemic risk, whereas physical risk shows no comparable relationship. Chabot and Bertrand (2023) simulate the effects of climate risk on European financial stability and conclude that both transition and physical risks can have adverse consequences, particularly through Scope 3 greenhouse gas emissions, temperature anomalies, heat waves, wildfires, and droughts. Finally, Birindelli et al. (2024), analysing 211 banks worldwide, find that institutions with stronger commitments to climate change, as reflected in their Carbon Disclosure Project scores, tend to display lower systemic risk, suggesting that proactive climate management can be a mitigating factor.

2.3. Climate initiatives and political risk in the context of climate finance

The first major initiative to advance the understanding of climate change and address its challenges was the establishment in 1988 of the Intergovernmental Panel on Climate Change (IPCC) by the United Nations Environment Programme (UNEP) in cooperation with the World Meteorological Organization. The panel's mission is to strengthen scientific knowledge on climate change and produce assessments that guide and shape policymaking. The description is presented in the present tense because the IPCC remains active, continues to be regarded by governments as an authoritative body, and regularly issues reports with substantial influence. Among its most notable publications is the *Special Report on Global Warming of 1.5°C*[1], a work closely linked to the Paris Agreement. Although many international initiatives exist (Seo, 2017), the Paris Agreement stands out for uniting 195 parties to limit global warming to well below 2°C, aiming for 1.5°C. Its adoption stimulated academic interest and influenced central banks, which, as Jabko and Kupzok (2024) note, began integrating climate concerns into policy discussions to support a low-carbon transition.

A major challenge in evaluating banks' exposure to fossil fuels and green finance is the limited transparency of available data. Europe, however, can be seen as a leading region in enhancing both disclosure practices and data accuracy. Relano et al. (2024) provide a global analysis of financing by banks to the largest oil companies, focusing on the post–Paris Agreement period, and propose metrics such as a carbon balance and a fossil fuel–to–equity ratio. Their descriptive evidence shows that the aggregate exposure of the largest U.S. banks remains significantly higher than that of other global banks. While there is broad

[1] The full resolution report is available at https://www.ipcc.ch/site/assets/uploads/sites/2/2022/06/SR15_Full_Report_HR.pdf

acknowledgment of the need for banks to redefine their corporate strategies in line with climate change objectives, determining the exact steps to achieve this is complex, particularly in countries whose economies depend heavily on fossil fuel industries. Waslander et al. (2021) identify five key actions for aligning banking activities with the Paris Agreement: developing robust systems for data collection and management, setting clear emissions-reduction targets, benchmarking clients' emissions performance, formulating explicit client engagement policies, and equipping relationship managers with the necessary expertise and tools on climate change.

Political decisions play a pivotal role, as government-driven climate policies largely shape how major economic actors, including banks, develop their strategies. Even within the same European regions, and despite widespread agreement on the importance of financing the transition to greener economies, national strategies differ considerably. Sweden, for example, in 2023 generated 66.4% of its total energy from renewable sources, far exceeding the European Union average of 24.5%.[2] The interplay between political agendas and banking sector involvement in climate-related financing has become an increasingly frequent subject of research. In some countries, such as the United States, political polarization on climate change is particularly pronounced. A survey by the PEW Research Center[3], in 2020 found that 78% of Democrats viewed climate change as a top priority, compared with only 21% of Republicans. Although financial markets are globally interconnected, the pace of the transition varies across regions, and political changes in one country do not necessarily lead to similar adjustments elsewhere. For example, during President Donald Trump's first term, known for his climate scepticism, European banks reduced, in relative terms, their lending to polluting firms in the United States, which, in contrast, benefited from support from the local government during that period (Reghezza et al., 2022).

[2] See for further details https://ec.europa.eu/eurostat/databrowser/view/nrg_ind_ren/default/table?lang=en
[3] Further details are available at https://www.pewresearch.org/short-reads/2020/02/28/more-americans-see-climate-change-as-a-priority-but-democrats-are-much-more-concerned-than-republicans/

3. The Systemic Risk of Leveraged and Covenant-Lite Loan Syndications

3.1. Introduction

In this paper, we study the systemic risk posed by leveraged and covenant-lite loans in the U.S. syndicated loan market. Leveraged loans are characterised by a high risk of default,[4] while covenant-lite loans offer lower repayment protection to the lender than standard loans. The syndicated loan market allows lenders to reduce large exposures to single borrowers, thus providing an opportunity for risk diversification. However, as lenders increasingly share exposures to the same pool of borrowers through loan syndications, they become more interconnected and, therefore, may be more prone to systemic risk. In this study, we investigate whether leveraged and covenant-lite loans contribute as a channel of systemic risk in the syndicated loans market. Our focus on leveraged and covenant-lite loans is driven by regulators' concerns that the quality standards of these loans have deteriorated over time.[5]

Dennis and Mullineaux (2000) show that syndicated lending is a "centuries-old process that has shown significant growth in the 1990s". Since it blossomed in the United States in the mid-1980s and with the launch of the Euro in the Euro area in 1999, syndicated lending has become one of the largest debt markets in developed economies.[6] Sufi (2007) notes that about 450 of the largest 500 non-financial firms in Compustat accessed the syndicated loan market between 1994 and 2002. This tendency can be explained partly by an increase in supply, as there has been a sharp increase in the number of small- and medium-sized lenders of loan syndications. Syndicated loans are attractive for small- and medium-sized lenders for two main

[4] Thomson Reuters defines as "leveraged" those loan syndications that satisfy specific criteria, includingan all-in drawn spread of at least 1.75% over LIBOR and a credit rating of BB+/Ba1 or lower (Thomson Reuters, 2018). Details can be found in the Appendix. An all-in drawn spread is defined in DealScan as the "total (fees and interest) annual spread paid over LIBOR for each dollar drawn down from the loan."

[5] For8mer Federal Reserve Chair, Janet Yellen, expressing concerns about the loosening standards of the $1.3tn market for leveraged loans said "I am worried about the systemic risks associated with these loans. There has been a huge deterioration in standards; covenants have been loosened in leveraged lending." (from The Financial Times article of October 25, 2018 titled "Janet Yellen sounds alarmed over plunging loan standards".)

[6] This market has become so relevant in some regions that a recent study by Acharya et al. (2018) demonstrates how the credit crunch in syndicated lending during the European debt crisis has affected the entire European economy in terms of investment, employment, and firms' sales growth.

reasons. As explained by Ivashina and Scharfstein (2010), participation in these syndicates allows lenders to share counterparty risk. Additionally, this market allows small-sized financial institutions to lend money to large borrowers who would otherwise be out of reach, by partnering with large financial institutions.

We contribute to the literature in two main ways. Firstly, we investigate the relationship between systemic risk and the exposure of both systemically important and non-systemically important banks to leveraged and covenant-lite syndicated loans. Our study covers the entire U.S. syndicated loans market and encompasses a significant time period from 2000 to 2022, which includes various recessions. By studying the connection between systemic risk and leveraged and covenant-lite lending, researchers and policymakers can identify which institutions are more vulnerable to credit shocks, and how they might transmit or amplify these shocks to other parts of the financial system. This can help in designing appropriate regulations, supervision, and macroprudential policies to mitigate the potential systemic risk arising from risky lending activities. For example, some possible policy measures could include imposing higher capital requirements, liquidity buffers, or risk retention rules for financial institutions that engage in leveraged lending, or enhancing the disclosure and transparency of the leveraged loan market and its participants.

The presence of systemic risk among the lenders in the syndication may be called into question by the practice of lead arrangers and other syndication lenders to sell part or all of their syndicated loan shortly after origination, as noted in Blickle et al. (2020). However, the same authors also find that lead arrangers tend to retain riskier loans to prevent reputation risk in case the loans go sour. This suggests that systemic risk may take the form of pipeline risk, which could be particularly relevant for leveraged loans and covenant-lite loans. The term pipeline risk refers to the potential risks associated with lenders retaining larger portions of loans considered less desirable or "cold". Bruche et al. (2020) suggest that using an indicator to measure each lender’s pipeline risk in connection with its leveraged loan exposure can guide stress tests and help determine appropriate the capital charges for bank loans. Indeed, leveraged and covenant-lite loans are more vulnerable to becoming "cold loans" during periods of market stress, as investors may become significantly more risk-averse and less willing to hold such exposures. The inability to readily offload these loans can expose syndicated loan lenders to heightened credit risk, liquidity risk, and funding challenges. This, in turn, may have destabilizing ripple effects on the stability of the whole financial system.

Our study shows that banks' systemic risk increases during recessions when banks are more exposed to leveraged syndicated loans. We assess this effect by introducing a new indicator, SN_RISK. This is defined as the bank's investment in risky syndicated loans as a proportion of the volume of risky loans in the syndicated loan market. Thus, SN_RISK measures how much market-wide syndication risk is borne by a particular institution at any given time. Our results confirm that SN_RISK helps to explain systemic risk variations across banks, during recession periods and specifically for systemically important institutions. Several papers investigate the syndicated loan market (Dennis and Mullineaux, 2000; Armstrong, 2003; Harjoto et al., 2006; Pascal and Franck, 2007; Ivashina and Scharfstein, 2010; Acharya et al., 2018; Dass et al., 2020). Only recently, however, academic research has started focusing on the systemic risk emerging from leveraged and covenant-lite lending. De Novellis et al.'s (2024) analyse leveraged finance in the banking sector and investigate systemic risk by developing novel indicators that capture credit risk exposure, bank size and interconnectedness. Our research differs from theirs in terms of measures, time-frame, and empirical analyses employed. Our results suggest that leveraged and covenant-lite loans are not inherently systemic, but they amplify systemic risk in the event of a crisis. While De Novellis et al. (2024) focus solely on globally systemically important banks (G-SIBs), our analysis encompasses the entire U.S. syndicated loans market. Further, we use a much more comprehensive sample of 33,406 unique syndicated leveraged and cov-lite loans obtained from Dealscan covering an extended period from 2000-2022, which includes the Great Recession. When using network analysis to model the interconnections in the syndicated loan market, our broader perspective reveals that although the number of network connections has decreased over the years, the relationship between the most influential banks in the network has actually intensified. As our findings indicate, this can amplify the spread of contagion effects in the event of a crisis.

Secondly, we contribute to the field of systemic risk analysis by applying an innovative approach developed by Blickle et al. (2020) to estimate lenders' post-origination exposure to syndicated borrowers. Other studies, such as Bruche et al. (2020) and Aramonte et al. (2022), show a notable decline in banks' lending share within the syndicated loan market after loan origination. Blickle et al. (2020)'s methodology allows us to calculate post-origination lending shares using Dealscan data across different types of syndicated loans (e.g. credit lines, term A and B loans) for both lead arrangers and other lenders in the syndicate. Interestingly, despite the introduction of this new methodology, the relative importance of top banks in the loan syndication sector remains largely unaffected. The observed effect primarily involves a redistribution of exposures, resulting in a reallocation of lending shares among lead arrangers and other lenders. However, this new approach enables us to determine holding shares with greater accuracy, thereby providing precise insights into the risk exposure and interdependence of financial intermediaries involved in the syndicated leveraged and covenant-lite lending. Wagner (2010), Raffestin (2014), and Cai et al. (2018) have established a correlation between loan syndications and systemic risk, demonstrating that strong similarities in banks' portfolios increase the likelihood of systemic crises. However, unlike Cai et al. (2018), who only consider lead arrangers and use strong assumptions to gauge their syndicated loan exposures, we consider all lenders in the syndication and estimate their post-origination exposure more accurately with the approach proposed by Blickle et al. (2020).

We employ network analysis to determine the importance, or network "centrality", of financial institutions within the syndicated loan market as a whole, and its leveraged and covenant-lite segments. Previous research has shown that network-based measures of interconnectedness are particularly well-suited to capture complex interactions among financial institutions (Hochberg et al., 2007; Larcker et al., 2013; Houston et al., 2018; Sümer and Özyıldırım, 2019; Bhattacharya et al., 2020; Guo et al., 2021; Asgharian et al., 2022). Our monthly panel regression analysis, tracking 96 global financial institutions from 2000 to 2022, confirms the significance of network centrality as an indicator of systemic risk. The presence of "hubs" or clusters of lenders who are highly interconnected through loan syndications, particularly involving financial institutions that regulators consider systemically important, is evident in our network representations. As a result, our findings could help enhance the methodology currently used by regulators to identify and rank systemically important financial institutions (Basel Committee on Banking Supervision (BCBS), 2018). This focus on network theory is consistent with other studies in the field. Allen and Babus (2009) argue that network theory improves our comprehension of financial systems. Using indirect measures of interconnectedness for a range of financial institutions, Billio et al. (2012) document an increased degree of interrelation in the financial system over time. Interest in financial networks is growing mainly due to their ability to demonstrate how the risk of financial contagion can propagate in the system. As indicated in Acemoglu et al. (2015), a financial system with a higher degree of connectivity is more resilient when faced with small shocks, but a high density of interconnections can facilitate the propagation of larger shocks, creating financial fragility in the system. We contribute to this literature by analysing the topology of the syndicated loans networks over time. Differently from Houston et al. (2018), we do not restrict the analysis to the 300 largest syndicated loan deals in the US market. Instead, we include the entire US syndication sample which enables us to consider also smaller players in the syndicated loan market. Our results show that the increasing presence of more peripheral financial institutions with low centrality decreases the average number of connections over time. However, there is an increasing propensity for more relevant banks in the network to collaborate with each other. This may lead to increased systemic risk stemming from systemically important financial institutions, particularly because of their exposure to leveraged and cov-lite loans, which may cause cascading losses in bad economic times.

We also add to the results of Asgharian et al. (2022) and show that in addition to the network centrality, the lender's exposure to leveraged and covenant-lite loans is a valid measure to assess the systemic importance of banks. Other studies in the literature contribute to a better understanding of the syndicated loan markets. For instance, Godlewski et al. (2012) apply network analysis to the French syndicated loan market, revealing that the structure of the French market allows for an improved flow of information and resources among institutions, which leads to lower loan spreads. Godlewski et al. (2012) results add to previous evidence obtained from network analysis regarding borrowing costs in relation to banks' interconnectedness, which is used as a proxy for banks' experience and reputation (Panyagometh and Roberts, 2010; Ross, 2010). Gao and Jang (2021) examine the structure of the global syndicated market and find that banks that are strictly regulated tend to collaborate with less regulated banks to engage in risky cross-border lending. Alperovych et al. (2022) focus on the leveraged buyout (LBO) segment of the syndicated market and show how the flow of information across the syndication network significantly determines the participation of a bank in the syndication, the amount it contributes to the syndication, and the terms of the loan.

We organise the remainder of the paper as follows. In Section 3.2, we describe our methodology, and Section 3.3 presents the data we use in our analysis. In Section 3.4, we report the main empirical findings and robustness tests, while Section 3.5 presents the conclusion.

Methodology

In this section, we describe the variables of interest and the econometric model used in our analysis. We present firm-level measures of interconnectedness based on network analysis and illustrate alternative definitions of SN_RISK, our measure of syndicated portfolio risk based on leveraged and covenant-lite loans. Our study employs the methodology proposed by Blickle et al. (2020) to calculate the risk exposure of lenders in the syndicated loan market. Unlike previous studies assuming that lead arrangers hold a 30% exposure to syndicated loans for at least 12 months (see for example Cai et al., 2018), Blickle and co-authors find that lead arrangers often sell their entire exposure within days of origination, resulting in a significant decrease in their syndicated loan portfolio. To account for this, we compute the share of syndicated loans held by lead arrangers and other participants immediately after origination using the methodology of Blickle et al. (2020).

We compare the differences in terms of ranking between lenders' shares calculated based on the methodologies proposed by Cai et al. (2018) and Blickle et al. (2020). These two methodologies are referred to, respectively, as Methodology A and Methodology B in Table 3.1, which reports the results for the top 10 financial institutions in the overall syndicated loans market (panel A) and its leveraged segment (panel B). Methodology A considers only lead arrangers whereas Methodology B covers all lenders in the syndication market. Although the rankings of the top 10 institutions using the two methodologies are similar, the overall market share of the very top banks falls drastically with Methodology B. For instance, the percentages of shares for the three leading banks, which are JP Morgan, Bank of America, and Citi, fall from 26.7%, 17.2% and 11.1% to 10.0%, 9.2%, and 6.3%, respectively. Interestingly, JP Morgan and Bank of America hold roughly 50% of their syndicated loans not as lead arrangers but as other types of lenders. Despite the differences, both methodologies reveal a significant concentration of exposure to the syndicated leveraged loan market, especially among financially systemically important institutions. Our findings regarding the systemic risk ranking of top banks in the syndicated loan market are consistent with the research conducted by Chu et al. (2019). Their results suggest that banks with a higher total capital ratio tend to have a stronger presence in loan funding compared to other banks participating in the same loan syndication. Notably, this relationship is more pronounced for systemically important banks, which are subject to more rigorous regulations and are mandated to maintain higher capital ratios than non-systemically important banks.

Table 3.1: Comparison of the top 10 financial institutions' ranking based on different methodologies

This table presents a comparison of the top 10 financial institutions based on their rankings in terms of syndicated loans (panel A) and syndicated leveraged loans amount (panel B). The comparison uses two methodologies: the commonly adopted approach before the introduction of the methodology by Blickle et al. (2020), and the methodology suggested by Blickle et al. (2020). The one called in the table Methodology A considers only lead arrangers and assumes they hold a 30% share of the total syndicated amount for a 12-month period. On the other hand, the one called Methodology B considers every lender in the syndicated market and allows for the estimation of a post-origination share by implementing the results derived from the regression analysis presented in the Blickle et al. (2020) paper, which is applicable to Dealscan data. In the latter case, the amount is held in the portfolio for 1 month. The period of analysis spans from 2000 to 2022.

Panel A. Syndicated loans market

Rank	Methodology A	Methodology A market share	Methodology B	Methodology B market share
1	JP Morgan	26.7%	JP Morgan	10.0%
2	Bank of America	17.2%	Bank of America	9.2%
3	Citi	11.1%	Citi	6.3%
4	Wells Fargo	4.9%	Wells Fargo	4.5%
5	Credit Suisse	3.9%	Deutsche Bank	3.2%
6	Deutsche Bank	3.0%	Credit Suisse	3.2%
7	Barclays	2.4%	Barclays	3.1%
8	Goldman Sachs	2.3%	Goldman Sachs	3.0%
9	Morgan Stanley	2.2%	Mitsubishi UFJ Financial Group	2.6%
10	Wachovia	1.6%	Morgan Stanley	2.2%

Panel B. Syndicated leveraged loans market

Rank	Methodology A	Methodology A market share	Methodology B	Methodology B market share
1	JP Morgan	19.8%	Bank of America	9.0%
2	Bank of America	17.0%	JP Morgan	8.7%
3	Credit Suisse	8.0%	Credit Suisse	5.4%
4	Citi	7.4%	Citi	5.0%
5	Deutsche Bank	5.8%	Wells Fargo	4.8%
6	Wells Fargo	5.1%	Deutsche Bank	4.3%
7	Goldman Sachs	3.7%	Goldman Sachs	3.9%
8	Barclays	3.6%	Barclays	3.3%
9	Morgan Stanley	2.9%	Morgan Stanley	2.6%
10	General Electric Capital	1.7%	Royal Bank of Canada	2.2%

3.2.1. Syndicated loan risk

To investigate the relationship between syndication risk and systemic risk, we introduce a novel measure of syndication risk that captures the importance of leveraged and covenant-lite loans held by a financial institution. Unlike previous studies, which typically assume that lead arrangers hold their share of syndicated loans for 12 months, we assume a one-month holding period based on the observation that lead arrangers in the syndicated loan market often sell their shares shortly after origination (Blickle et al., 2020).

For each lender i and month t, we define the amount of leveraged but not covenant-lite loans issued over a one-month period as $Lev_{i,t}$, the issued amount of covenant-lite but not leveraged loans as $CovLite_{i,t}$, and the amount of loans that are simultaneously leveraged and covenant-lite as $Lev\&CovLite_{i,t}$. We then propose two main versions of SN_RISK, which serve as our new measures of syndicated portfolio risk. Each version accounts for the riskiness of the syndicated loan portfolio of the lender as well as the lender's market share of the overall syndicated loan market. The first is $SN\_RISK_{i,t}^{Lev}$, which measures the amount of leveraged loans (which may or may not be covenant-lite) held by lender i divided by the total syndicated leveraged issuance amount in the market.

$$SN\_RISK_{i,t}^{Lev} = \frac{Lev_{i,t} + Lev\&CovLite_{i,t}}{Lev_t + Lev\&CovLite_t} \tag{1}$$

The second, $SN\_RISK_{i,t}^{Lev\&CovLite}$, also considers covenant-lite loans that are not leveraged:

$$SN\_RISK_{i,t}^{Lev\&CovLite} = \frac{Lev_{i,t} + Lev\&CovLite_{i,t} + CovLite_{i,t}}{Lev_t + Lev\&CovLite_t + CovLite_t} \tag{2}$$

Both measures vary between 0 and 1 by construction. We perform various robustness tests by utilizing alternative versions of the two main measures described above. These alternative measures are discussed in detail in Section 3.4.2.

3.2.2. Measures of interconnectedness

Given the presence of common loans among banks, the syndicated loan market is well-suited for representation as a network. A network is composed of nodes and edges: the nodes are the lenders participating in loan syndications, while each edge (or linkage) connects two lenders in the same syndicate. We build monthly syndicated loan networks by following the standard framework for undirected networks. Let $N = 1,2,3, \dots, n$ be the lenders who compose a syndicate. We first build the undirected network G with the set of nodes $V(G) = v_1, v_2, \dots, v_v$. The $v \ x \ v$ adjacency matrix $A(G)$ represents the edges between nodes (i.e., lenders) i and k (where $i \neq k$) in the syndicated loan market. The adjacency matrix is symmetric, as the connections are between lender i and k or, equivalently, lender k and i. Based on the connection between lenders i and k within 12 months prior to month t, each element of the adjacency matrix is equal to

$$a_{i,k} = \begin{cases} 1, \text{if an edge between lenders } i \text{ and } k \text{ exists,} \\ 0, \text{if an edge between lenders } i \text{ and } k \text{ does not exist,} \end{cases}$$

From each monthly syndicated network, we compute three measures of centrality, which we employ as proxies for interconnectedness in our regression analysis. The first measure is the degree of (normalised) centrality, which is defined as follows:

$$Degree_{i,t} = \left(\frac{\sum_k a_{i,k,t}}{N-1} \right) * 100, \tag{3}$$

where N is the total number of nodes in the network. Intuitively, the higher the number of connections of a financial institution, the higher its degree of centrality.

The second measure, called closeness centrality, measures the proximity between a node and the others.

$$Closeness_{i,t} = \frac{1}{\sum_k d_{i,k,t}}, \tag{4}$$

where $d_{i,k,t}$ is the distance (length of the shortest path) between node i and node k.

The last measure, called eigenvector centrality, is also a measure of how influential a lender is in the network. However, in eigenvector centrality, linkages are weighted by the importance of the other institutions to which a lender is connected in the network. Intuitively, if two lenders have an equal number of connections, the one connected with more "influential" nodes – i.e., lenders with higher connectivity – will have higher eigenvector centrality. To obtain the eigenvector centrality of institution i, we first identify the largest eigenvalue λ of $A(G)$ and the corresponding eigenvector $x_{i,t}$. Then, we scale the elements of $x_{i,t}$ so that its largest element is 1. The eigenvector centrality of institution i will then be the $i - th$ element of $x_{i,t}$.

3.2.3. Systemic risk measures

Multiple systemic risk measures are available in the literature (Bisias et al., 2012; Ellis et al., 2021). In this study, we employ the $SRISK$ measure developed by Acharya et al. (2017) and Brownlees and Engle (2017). $SRISK$ depends on the size of a firm, its leverage, and the loss in equity capital the firm is expected to suffer in a systemic crisis, which is characterised by a market drop of more than 40% over six months. $SRISK$ is calculated as follows:

$$\begin{aligned} SRISK &= E(k(D + MV) - MV \mid Crisis) \\ &= kD - (1 - k)(1 - LRMES)MV \end{aligned} \tag{6}$$

where k is the regulatory capital requirement, D is the book value of debt which is calculated as the difference between the book value of assets and the book value of equity and does not change during the crisis period, $LRMES$ (Long-Run Marginal Expected Shortfall) is the expected fractional loss of the firm equity when the market index declines significantly in a six-month period[7]; MV is the current market capitalisation of the firm.

[7] It is calculated as $(1 - exp(log(1 - d) * beta)$, where d is the six-month crisis threshold for the market index decline and its default value is 40% (the threshold reflects the drop experienced in the financial market during the financial crisis of 2007–2009.); and beta is the firm's CAPM beta.

3.2.4. Model

We estimate several models to analyse the relationship between the systemic risk of global financial institutions and the novel measures of network centrality and syndicated leveraged and covenant-lite loan risk. In our main regression analysis, we employ as dependent variable the first difference of $SRISK$ in billions of U.S. dollars (hereafter called $\Delta SRISK$) to address the non-stationarity of $SRISK$, particularly during periods of recession.

The general form of the estimated panel regression is as follows:

$$\begin{aligned}\Delta \mathrm{SRISK}_{i,t} = \alpha &+ \beta_1(\mathrm{SN\_RISK}_{i,t-1} * \mathrm{USRecession}_t) \\ &+\beta_2(\mathrm{SN\_RISK}_{i,t-1} * \mathrm{USNon-Recession}_t) \\ &+\beta_3(\mathrm{Interconnectedness}_{i,t-1} * \mathrm{USRecession}_t) \\ &+\beta_4(\mathrm{Interconnectedness}_{i,t-1} * \mathrm{USNon-Recession}_t) \\ &+\beta_5(\mathrm{TotalAssets}_{i,t-1}) \\ &+\beta_6(\mathrm{MarketSize}_{i,t-1}) \\ &+\beta_7(\mathrm{LaggedSRISK}_{i,t-1}) + \mathrm{FixedEffects}_i + \varepsilon_{i,t}\end{aligned} \tag{7}$$

where, in addition to SN_RISK, we add as controls the one-month lagged lender's size measured as Total Assets in billion dollars ($)[8]; the Market Size of the syndicated loan market in billion dollars; and the one-period lagged SRISK. To investigate whether highly central financial institutions in a syndicated network are more vulnerable to systemic risk during recessions, we use the three measures of centrality obtained from network analysis and presented in Section 3.2.2. Recession is the National Bureau of Economic Research (NBER)-based U.S. recession dummy variable. We estimate regressions with bank fixed effects to control for unobserved heterogeneity among lenders in our sample. Standard errors are clustered at the bank level. Although the model's dependent variable is the first difference of $SRISK$, we add $SRISK$ at time t-1 as a control variable to address any persistent effects that may be present in the data. As

[8] We employ quarterly data whenever available and project them to the following months until the next available data point. In cases where quarterly accounting information is not available, we rely on semi-annual or annual data instead.

pointed out in Cai et al. (2018), systemic risk exhibits high persistence over time. This means that certain underlying factors, such as changes in the economic or regulatory environment, could lead to a persistent trend in the data that may not be fully controlled by simply taking the first difference of $SRISK$. By including the lagged value of $SRISK$ as a control variable, we account for these persistent effects.

3.3. Data

The data used to construct the variables employed in the regression analysis are gathered from various sources. Our main dataset consists of daily U.S. syndicated loans obtained from the Thomson Reuters DealScan database. We focus our analysis on the U.S. market for two main reasons. Firstly, the United States alone accounts for nearly half of the outstanding amount of global syndicated loans and has a 72% share of the global leveraged loan amount issued worldwide over the period 2000-2022. Secondly, the framework proposed by Blickle et al. (2020) to estimate each lender's share in the syndication is developed by considering specifically the U.S. market.

The DealScan database provides comprehensive coverage of loans issued to U.S. borrowers by international financial institutions. We extract a large set of variables to develop our main analysis, such as borrowers' name, location of headquarter at the state level and industry sector, the set of lenders participating in the loan syndication and their respective shares, and several loan details including the market segment to which they belong (i.e. leveraged, highly leveraged, covenant-lite), the interest rates charged and the presence of covenants. Appendix A reports the Thomson Reuters description of the criteria used to identify the high-risk loans that are included in the leveraged category. Table A. 3.1 in the Appendix provides a brief description of the key DealScan variables used in this analysis. Table 3.2 reports descriptive information about the U.S. syndicated loans during 2000–2022, with a breakdown by leveraged, covenant-lite, and both leveraged and covenant-lite loans. When considering the syndicated loans' total issuance amount, we can see that from 2003 to the eve of the financial crisis, the market grew significantly. This growth was mainly driven by the booming trend in the U.S. economy, which experienced a long period of economic expansion during these years.

However, the syndicated loan market reversed its trend with the global financial crisis when the issuance amount decreased significantly by about 71%. Over the three-year period from 2007 to 2009 there was also a noticeable decline in the number of unique borrowers (-53%) and unique loans (-55%). As noted by Ivashina and Scharfstein (2010), the fall in the issuance amount was observed across all common types of syndicated loans, including term loans, investment grade, and non-investment grade loans. Additionally, Giannetti and Laeven (2012) found that the collapse in the global syndicated market during this period was characterised by a "flight home effect," where lenders preferred to issue loans to local borrowers instead of funding overseas transactions. However, in the years following the global financial crisis, the market bounced back, with syndicated loans reaching a total value of $1.5 trillion issued in 2022. The trend of the syndicated leveraged loan market followed a slightly different pattern, with the issuance amount reaching a peak of almost $1 trillion on the eve of the financial crisis and accounting for almost half of the syndicated loans issued in the U.S. market in 2007. During the global financial crisis, the issuance amount of leveraged loans sharply declined, reaching its lowest point of about $249 billion in 2009. While the market rebounded in the following years, the amount of leveraged loans remained below the 2007 level. However, the share of leveraged loans relative to the total market in the post-crisis period often surpassed pre-crisis levels. Figure 3.1 illustrates these trends. The covenant-lite market also experienced a peak in 2007, with a total amount of $110 billion. However, there are no syndicated covenant-lite loans recorded in the DealScan database prior to 2005, and during the global financial crisis, covenant-lite loans nearly disappeared. Since 2011, the covenant-lite market has been on the rise again, increasing from $44 billion to $149 billion in 2022, and accounting for almost 10% of the total syndicated loans market. Table 3.3 presents the distribution of borrowers by industrial sector in the entire syndicated loans market (Panel A) as well as the leveraged (Panel B) and covenant-lite segments (Panel C). The top sectors across the three panels are manufacturing, finance, insurance, real estate, transportation, public utilities, and services. In particular, the services sector is among the most prominent in the leveraged and covenant-lite segments. According to the findings of Blickle et al. (2023), the banks' extensive specialisation in particular industries can be attributed to their industry-specific expertise, leading them to prioritize their preferred industry in their lending activities.

Table 3.2: U.S. syndicated loan market: historical trends

This table presents historical trends for the U.S. syndicated loan market and its leveraged and covenant-lite segments. All figures are computed yearly. The issuance amount represents the sum of the principal loan amounts issued during each year. The shares of leveraged, covenant-lite, and simultaneously leveraged and covenant-lite loans are expressed as percentages of the total syndicated loan issuance amount.

	All syndicated loans			***Of which:*** **Leveraged loans**				**Cov-lite loans**				*Simultaneously* **leveraged & cov-lite loans**			
Year	TOT SN issuance amount (B$)	N. unique borrowers	N. loans	Share (as % of TOT SN issuance amount)	Issuance amount (B$)	N. unique borrowers	N. loans	Share (as % of TOT SN issuance amount)	Issuance amount (B$)	N. borrowers	N. loans	Share (as % of TOT SN issuance amount)	Issuance amount (B$)	N. unique borrowers	N. loans
2000	1,236	3,322	3,811	25.5%	315	1,673	1,846					25.5%	315	1,673	1,846
2001	1,198	3,014	3,472	20.3%	243	1,424	1,529					20.3%	243	1,424	1,529
2002	1,041	2,991	3,432	25.3%	264	1,482	1,618					25.3%	264	1,482	1,618
2003	965	3,191	3,623	33.7%	325	1,621	1,818					33.7%	325	1,621	1,818
2004	1,395	3,765	4,296	35.3%	493	2,005	2,278					35.3%	493	2,005	2,278
2005	1,711	3,923	4,431	35.5%	608	1,882	2,105	0.1%	2	4	5	35.5%	608	1,882	2,105
2006	1,880	4,003	4,496	36.9%	694	1,950	2,169	1.1%	21	45	45	36.9%	694	1,950	2,169
2007	2,100	3,703	4,148	45.5%	957	1,854	2,050	5.2%	110	129	133	46.0%	967	1,858	2,055
2008	927	2,420	2,646	41.7%	386	1,233	1,325	0.4%	4	1	1	41.7%	386	1,233	1,325
2009	604	1,743	1,882	41.3%	249	965	1,030	0.1%	1	1	1	41.3%	249	965	1,030
2010	1,041	2,402	2,579	36.5%	380	1,183	1,266	0.5%	5	6	6	36.5%	380	1,183	1,266
2011	1,181	2,394	2,531	33.3%	393	1,191	1,241	3.8%	44	49	50	33.4%	395	1,191	1,242
2012	1,071	2,540	2,706	46.4%	497	1,384	1,477	5.7%	61	92	93	46.4%	497	1,385	1,478
2013	1,276	2,490	2,664	56.5%	721	1,539	1,636	21.4%	273	237	250	57.7%	737	1,543	1,642
2014	1,318	2,529	2,684	46.2%	609	1,436	1,502	17.9%	236	270	272	46.9%	618	1,441	1,508
2015	1,300	2,316	2,461	42.1%	548	1,177	1,228	12.8%	166	173	179	42.2%	549	1,179	1,231
2016	1,178	2,124	2,208	42.0%	495	1,045	1,080	15.2%	179	157	162	42.2%	497	1,046	1,082
2017	1,192	2,161	2,265	49.5%	590	1,161	1,223	23.4%	279	287	296	50.1%	598	1,166	1,228
2018	1,522	2,234	2,342	41.6%	633	1,115	1,155	17.9%	273	302	304	41.9%	638	1,118	1,158
2019	1,135	2,121	2,204	40.0%	454	971	1,012	16.2%	184	186	192	41.3%	468	984	1,025
2020	1,079	1,905	2,028	40.8%	440	810	850	15.3%	165	142	145	42.6%	460	819	861
2021	1,679	2,513	2,621	46.0%	772	1,155	1,187	16.7%	280	286	285	46.4%	780	1,165	1,199
2022	1,514	2,150	2,255	31.5%	477	687	713	9.8%	149	110	113	31.6%	479	689	713

Figure 3.1: U.S. syndicated loans market

This figure represents the size of the U.S. syndicated loans market from 2000 to 2022, with a breakdown for the leveraged loans. The market size is measured by the total newly originated syndicated loan amount during the year in billions of U.S. dollars.

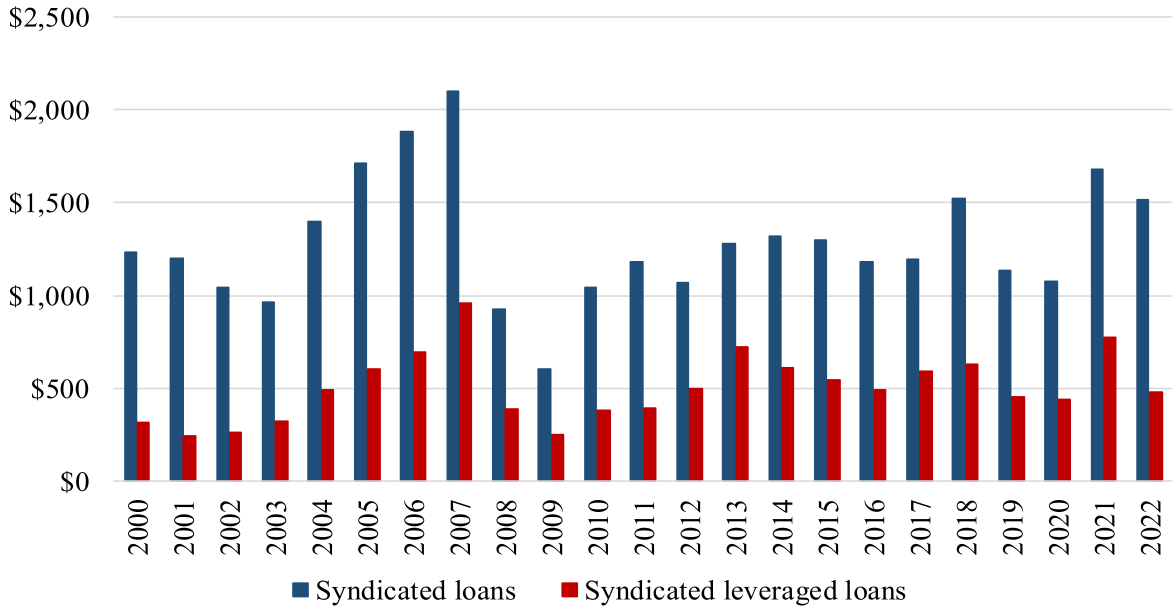


Table 3.3: Description of the U.S. syndicated loan market by industry and loan type

This table presents the share of the syndicated loan market represented by each industrial sector, computed as the ratio between the issuance amount to borrowers belonging to that sector and the total issuance amount for each sample sub-period. Shares are computed over time for the following sub-periods: 2000–2004, 2005–2007, 2008–2010, 2011–2013, 2014–2016, 2017–2019, and 2020–2022. Panels A, B, and C refer to the entire syndicated loan market, the leveraged segment, and the covenant-lite segment, respectively.

Panel A. Syndicated loans

	SIC code and descprition	2000-2004	2005-2007	2008-2010	2011-2013	2014-2016	2017-2019	2020-2022
(20–39)	Manufacturing	28.2%	26.7%	30.3%	28.7%	30.5%	31.8%	28.5%
(60–67)	Finance, Insurance, Real Estate	23.8%	20.0%	18.5%	18.0%	18.3%	18.3%	19.5%
(40–49)	Transportation & Public Utilities	22.1%	18.5%	17.5%	17.1%	15.6%	13.4%	12.8%
(10–14)	Mining	4.1%	6.8%	8.0%	6.7%	4.2%	5.2%	3.0%
(70–89)	Services	11.1%	15.4%	13.4%	18.1%	19.0%	21.6%	24.4%
(52–59)	Retail Trade	4.9%	6.0%	6.2%	5.4%	6.8%	4.5%	5.4%
(50–51)	Wholesale Trade	3.0%	3.2%	3.7%	4.1%	4.0%	3.4%	3.6%
(91–97)	Public Administration	0.4%	0.1%	0.2%	0.2%	0.1%	0.1%	0.1%
(15–17)	Construction	1.5%	2.5%	1.4%	0.9%	0.7%	1.0%	1.7%
(01-09)	Agriculture, Forestry, Fishing	0.8%	0.7%	0.9%	0.8%	0.8%	0.8%	1.0%
Total syndicated loans issuance amount ($B)		5,750	5,608	2,546	3,462	3,769	3,845	4,194

Panel B. Syndicated leveraged loans

	SIC Code and Descprition	2000-2004	2005-2007	2008-2010	2011-2013	2014-2016	2017-2019	2020-2022
(20–39)	Manufacturing	35.3%	30.6%	31.0%	27.3%	28.0%	25.3%	23.7%
(60–67)	Finance, Insurance, Real Estate	8.6%	6.9%	8.0%	9.9%	9.2%	11.0%	11.7%
(40–49)	Transportation & Public Utilities	21.2%	21.3%	16.0%	14.8%	12.2%	13.1%	9.6%
(10–14)	Mining	4.3%	4.9%	9.1%	6.9%	4.8%	5.7%	3.7%
(70–89)	Services	15.5%	22.4%	20.5%	26.3%	27.8%	30.4%	36.2%
(52–59)	Retail Trade	7.5%	6.9%	8.3%	6.9%	10.4%	6.6%	6.3%
(50–51)	Wholesale Trade	5.4%	5.3%	5.8%	6.2%	6.1%	5.6%	5.6%
(91–97)	Public Administration	0.2%	0.1%	0.1%	0.2%	0.1%	0.1%	0.2%
(15–17)	Construction	0.6%	0.7%	0.3%	0.4%	0.4%	1.0%	1.2%
(01-09)	Agriculture, Forestry, Fishing	1.3%	0.9%	0.9%	1.1%	1.1%	1.2%	2.0%
Total syndicated leveraged loans issuance amount ($B)		1,613	2,222	1,004	1,578	1,642	1,675	1,645

(Table 3.3 - continues in the next page)

(Table 3.3 - continued)

Panel C. Syndicated covenant-lite loans

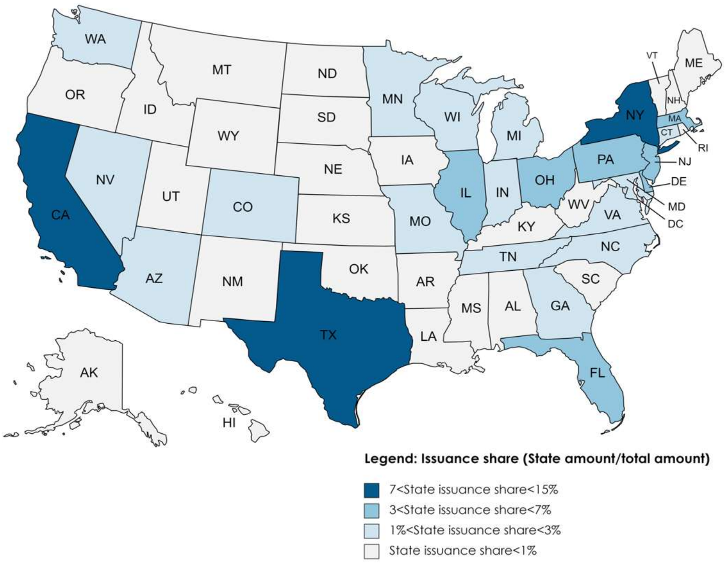
	SIC Code and Descprition	2005-2007	2008-2010	2011-2013	2014-2016	2017-2019	2020-2022
(20–39)	Manufacturing	30.9%	67.2%	28.2%	27.7%	24.9%	21.8%
(60–67)	Finance, Insurance, Real Estate	5.5%		6.3%	6.9%	7.7%	10.3%
(40–49)	Transportation & Public Utilities	21.3%		11.5%	9.3%	13.0%	10.4%
(10–14)	Mining	7.2%		4.6%	3.0%	2.1%	0.7%
(70–89)	Services	18.2%	7.2%	29.2%	32.5%	39.4%	43.4%
(52–59)	Retail Trade	10.8%	19.9%	10.5%	12.8%	6.1%	5.7%
(50–51)	Wholesale Trade	4.3%		7.4%	6.7%	4.2%	4.7%
(91–97)	Public Administration			0.1%			0.1%
(15–17)	Construction	1.1%		0.6%	0.3%	1.5%	0.8%
(01-09)	Agriculture, Forestry, Fishing	0.8%	5.7%	1.6%	0.9%	1.2%	2.0%
Total syndicated covenant-lite loans issuance amount ($B)		133	10	375	581	735	584

Figure 3.2 represents the geographical distribution of the overall syndicated market (Panel A) and leveraged market (Panel B) across the United States. We can see that Panels A and B are highly similar and indicate that the strongest concentration of the syndication activity is in the states of California, Texas, and New York, with Illinois, Pennsylvania, and Florida following closely behind. Unsurprisingly, these states also correspond to the ones which contribute the most to the aggregate U.S. gross domestic product. While the borrowers in our sample are headquartered in the United States, the lenders are both U.S. and international. We observe a strong presence of large global financial institutions among the top active lenders, many of which are systemically important banks. We adjust for the mergers and acquisitions (M&As) that occurred in the financial sector during the sample period. This adjustment is done to identify lenders at parent company level as reliably as possible. For example, Merrill Lynch was acquired by Bank of America in September 2008. However, in the Thomson DealScan data, the most recent parent, in other words, Bank of America, is retroactively assigned to all Merrill Lynch transactions back to the start of the sample. We correct the data by considering acquired companies as separate entities until their acquisition. To do so, we manually merge the syndicated loans database with the M&A Thomson One database, which includes historical details of M&A activity.

Figure 3.2: Syndicated loans across the United States

This figure represents the borrower distribution by issuance amount across the United States. For each state, we indicate the issuance share, which is calculated as the ratio between the amount issued to borrowers in that state and the total issuance amount in the market. The issuance share is also colour-coded, with the darkest colour indicating the highest shares as detailed in the legend. The share of unique borrowers across states, which is calculated by dividing the number of unique borrowers in each state by the total number of borrowers in the United States, is presented on the tables on the right-side. The period of the analysis is January 2000–December 2022. Panels A and B represent the entire syndicated market and its leveraged segment, respectively.

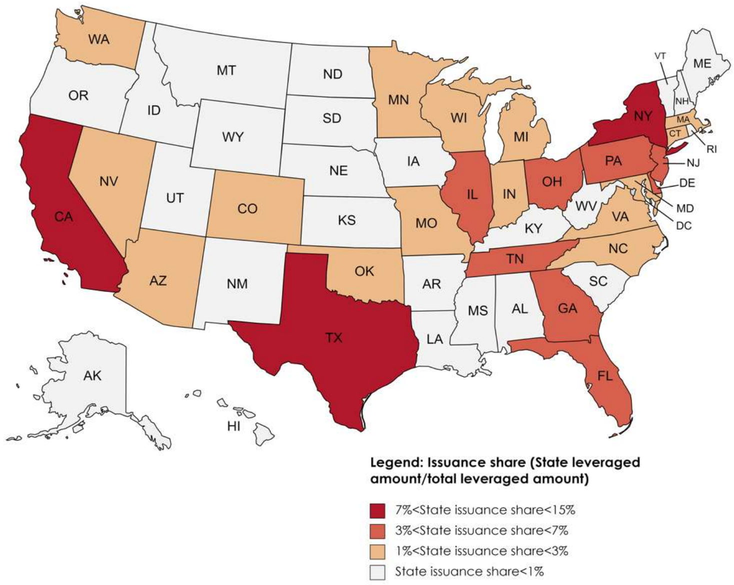
Panel A. Syndicated loans market



$$\text{Borrowers share distribution} = \frac{\mathit{State's\ number\ of\ unqiue\ borrowers}}{\mathit{Total\ number\ of\ unique\ borrowers}}$$

Texas	10%
California	10%
New York	7%
Delaware	6%
Illinois	5%
Florida	5%
Pennsylvania	3%
Massachusetts	3%
Ohio	3%
New Jersey	3%
Other	45%

Panel B. Syndicated leveraged loans market



$$\text{Borrowers share distribution} = \frac{\mathit{State's\ number\ of\ unqiue\ borrowers}}{\mathit{Total\ number\ of\ unique\ borrowers}}$$

Texas	12%
California	11%
New York	7%
Delaware	6%
Illinois	5%
Florida	5%
Pennsylvania	4%
Ohio	4%
New Jersey	3%
Georgia	3%
Other	40%

3.3.1. Syndicated loan networks

Figure 3.3 provides a graphical representation of the syndicated market using network analysis. Panel A depicts the market in the year 2007, which corresponds to the period of highest syndication activity between 2000 and 2022. Panel B shows the year 2009, which represents the lowest peak of syndicated lending due to the global financial crisis. Additionally, we include the years 2013 and 2021 in the analysis, which are characterised by the second and third highest amounts of leveraged loan issuance, respectively. The analysis includes all banks that are active in the U.S. syndication market during the reference period, including both systemically and non-systemically important institutions.

In each graph, the nodes are red-coloured if a lender is considered globally systemically important, green-coloured if it is domestically systemically important, and blue-coloured if it does not belong to these groups. As described in Section 3.2.2, there is an edge between lenders i and k when they are both part of the same syndication. However, in Figure 3.3, we depict two edges per transaction to highlight the systemic importance of the lenders. Specifically, if both lenders are systemically important, both edges are pink-coloured. If one bank is systemically important and the other is not, one edge is pink-coloured and the other is blue-coloured. If both banks are non-systemically important, both edges are blue-coloured. Furthermore, the dimension of the node indicates the lender's share of leveraged and covenant-lite loans within the market.

We can see that these networks are characterised by a complex system of relationships. The four years represented reveal the presence of lenders that correspond to the definition of "hubs". These hubs are the most central and active financial institutions that play a crucial role in creating loan relationships in the syndication market. This is particularly evident for banks such as Bank of America, J.P. Morgan, Wells Fargo, and Citi, as well as other systemically important banks. Indeed, their high connectivity is one of the key factors that place them among the globally systemically important banks identified by regulators following the global financial crisis.[9] However, the topological features of the networks also raise concerns about the concept

[9] For example, see the 2019 list of globally systemically important banks (G-SIBs) published by the Financial Stability Board on https://www.fsb.org/2022/11/2022-list-of-global-systemically-important-banks-g-sibs/

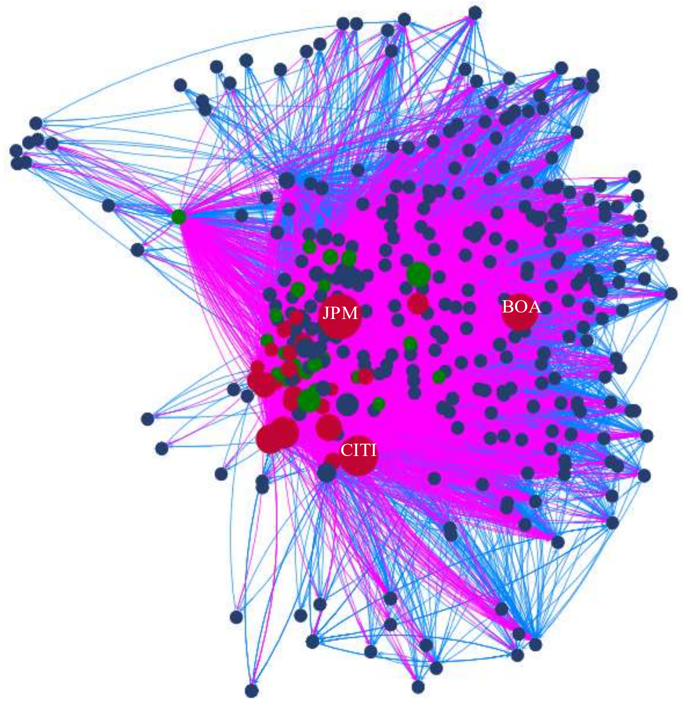
of "too interconnected to fail," which is used to identify super-spreaders in the market (Markose et al., 2012). The high degree of interconnectedness could be a potential source of systemic risk as it may mean that shocks can propagate quickly through the market.

Figure 3.4 presents the median degree, closeness, and eigenvector centrality trends spanning the years 2000 to 2022 across all lenders in the U.S. syndicated loans market. Panel A shows the median centrality for the entire sample of banks, while Panel B focuses on systemically important financial institutions. The three graphs in Panel A collectively indicate a consistent overarching pattern in the evolving median influence of nodes within the network graph over time. They show an initial gradual decline during the period spanning 2000-2004, followed by a gradual ascent that reaches its peak in 2010 for all three centrality metrics. After this peak, there is a progressive decline from 2011 to 2022 across all three measures, falling below the levels observed before the financial crisis. This decreasing trend indicates reduced interconnectedness during this period compared to the pre-financial crisis era, influenced by the heightened presence of numerous peripheral financial institutions that, on average, have lower levels of connectivity with other entities in the market. However, the trend of the median eigenvector centrality of systemically important financial institutions, represented in Panel B3, shows an overall increase over the sample period of 24.9%. Eigenvector centrality considers both the number of connections a node has and the importance of the nodes to which it is connected. Despite the growing participation of smaller lenders with low centrality in the syndication market, this result suggests that systemically important institutions tend to collaborate more with other institutions in the network.

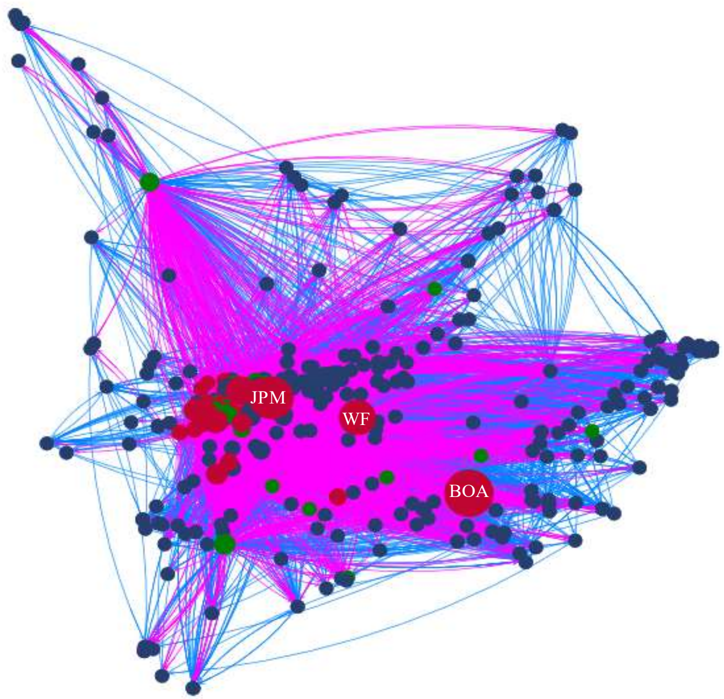
Figure 3.3: Syndicated loan networks

This figure represents the two U.S. global syndicated loan networks in 2007 (Panel A), 2009 (Panel B), 2013 (Panel C) and 2021 (Panel D) for the U.S. syndicated loans market. In the graphs, nodes of different colours denote institutions with a different degree of systemic importance. There are two connection lines (edges) between each pair of nodes. If both lenders are systemically important, both edges are pink-coloured. If one lender is systemically important and the other is not, one edge is pink-coloured and the other one is blue-coloured. If both lenders are not systemically important, both edges are blue-coloured. The dimension of the node indicates the lender's share of leveraged and covenant-lite loans within the market.

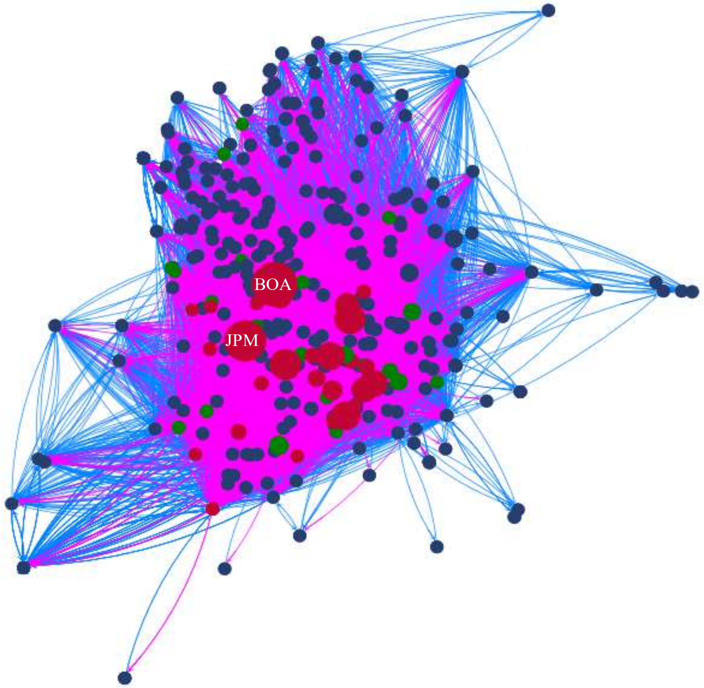
Panel A. Year 2007



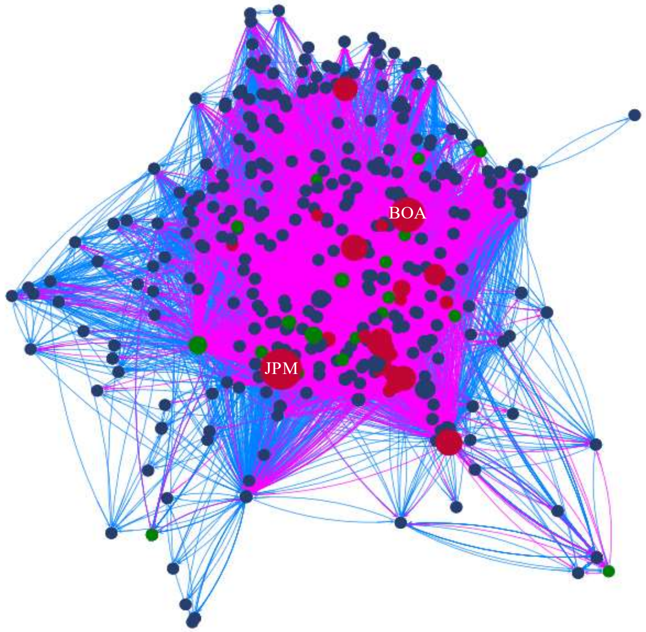
Panel B. Year 2009



Panel C. Year 2013



Panel D. Year 2021



Colors legend

- Globally Systemically Important Banks (G-SIBs)
- Domestically Systemically Important Banks (D-SIBs)
- Other Financial Institutions

Nodes legend

BOA: Bank of America

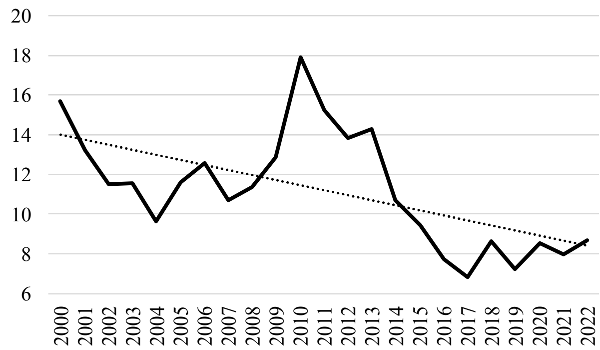
WF: Wells Fargo

JPM: JP Morgan

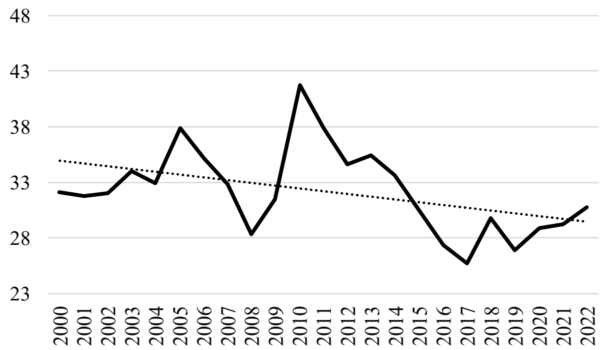
Figure 3.4: Median degree, closeness and eigenvector centrality

This figure depicts the annual median values for degree centrality and eigenvector centrality of all lenders in the U.S. syndicated market over the sample period 2000–2022, with a breakdown for systemically important institutions. The dotted lines are the linear trends estimated from the centrality data reported in the figures. Panel A shows the month-by-month median values of the network centrality measures for the entire sample of financial institutions, while panel B shows median values only for the subsample of systemically important financial institutions.

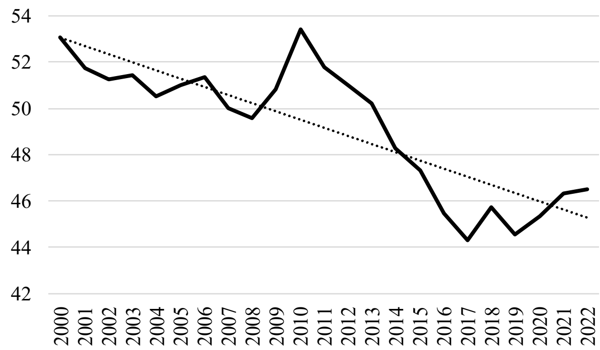
Panel A1. Median degree centrality



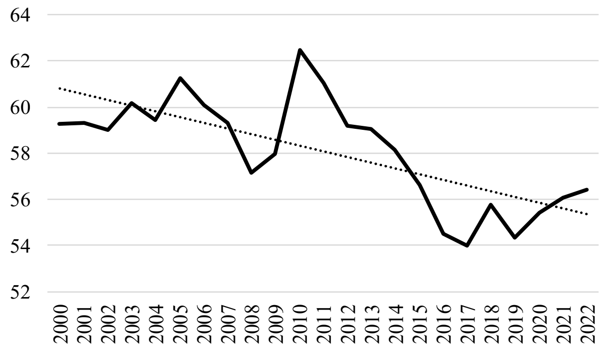
Panel B1. Median degree centrality of SIFIs



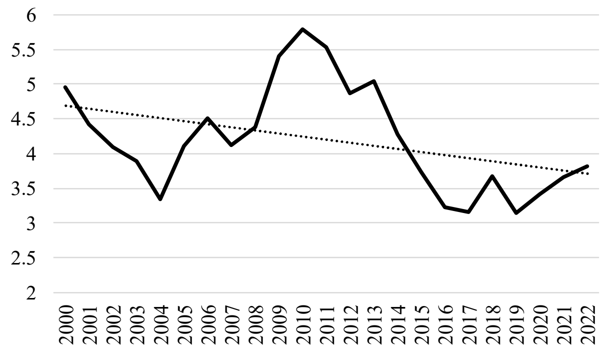
Panel A2. Median closeness centrality



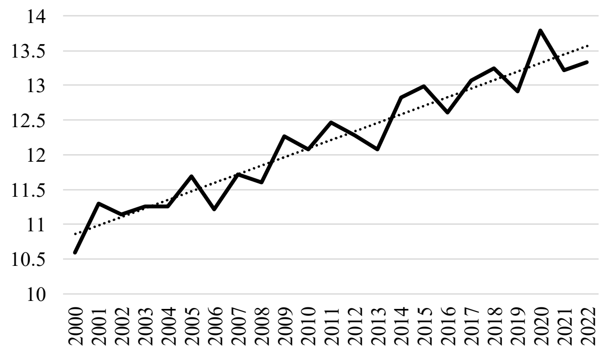
Panel B2. Median closeness of SIFIs



Panel A3. Median eigenvector centrality



Panel B3. Median eigenvector centrality of SIFIs



3.3.2. Other data

To develop our main analysis, we gather additional data from external sources and merge them into our dataset. In order to account for the potential impact of regulatory metrics on systemic risk, we obtain Risk Adjusted Capital TIER1, Risk Adjusted Capital TIER2, and loan loss provision data from the Orbis database. To determine whether our main results are robust to alternative definitions of recession periods, we consider two recession dummies based on the U.S. business cycle expansions and contractions data provided by the NBER. In particular, in our main regression, we employ the USRECD variable computed with the "peak method", which identifies as recessions the periods from April 2001 to November 2001, from January 2008 to June 2009, and from March to April 2020. In the robustness tests, we use the USRECDM dummy, which is based on the "trough method", in which recessions are dated from March 2001 to October 2001, and December 2007 to May 2009, and February to March 2020. To further investigate the role played by systemically important financial institutions (SIFIs) in our sample, we control for their effect with a dummy variable that takes a value of 1 if the financial institution is classified by regulators as either a globally or domestically systemically important bank. We gather the full set of systemically important institutions from different sources.[10] This analysis is subject to the limitation that the regulatory list of systemically important institutions became available only after the global financial crisis. To overcome this limitation, we assume that each institution identified as systemically important after the financial crisis is also systemically important before the crisis. We have also labelled as systemically important Lehman Brothers and Bear Stearns, which collapsed during the global financial crisis.

[10] The main list is gathered from the database published by the Bank for International Settlement on https://www.bis.org/bcbs/gsib/gsib_assessment_samples.htm. We integrate the list with the information found in country-based official sources: https://www.mas.gov.sg/news/media-releases/2015/mas-publishes-framework-for-domestic-systemically-important-banks-in-singapore; Australian Prudential Regulation Authority, 2013; Basel Committee on Banking Supervision, 2016; Financial Stability Board, 2013; Financial Stability Board, 2016; Reserve Bank Of India, 2019.

3.4. Results

In our main regressions, we investigate the role of syndication risk and network centrality in explaining changes in an institution's systemic risk. While network centrality measures offer valuable insights into the structure and influence of the syndicated market, our novel measure of syndication risk assesses the degree of risk-taking of a lender in the leveraged and covenant-lite market. The main variables of interest are interacted with a recession dummy and a non-recession dummy to control for business cycle effects.

As shown in Table 3.4, the coefficients of $SN\_RISK_{i,t-1}^{Lev}$ and $SN\_RISK_{i,t-1}^{Lev\&CovLite}$ interacted with the recession dummy are positive and statistically significant across all specifications. These results suggest a greater impact of syndication risk on systemic risk during periods of economic recession compared to non-recession periods. The economic impact is also significant. Specifically, when SN_RISK increases by one standard deviation during recessions, the estimated increase in the mean $SRISK$ variation is around 25% to 31%, considering at least the previous six months of the US economy being characterised by a recession. This finding indicates that in the event of a future financial crisis, losses in the leveraged and covenant-lite markets could worsen the severity of the crisis. Additionally, higher interconnectedness, as captured by degree, closeness and eigenvector centrality, is associated with higher systemic risk. However, these relationships reveal consistently strong statistical significance only during periods of recession. The results for the three centrality measures are robust when we introduce the measures of SN_RISK, in addition to the centrality measures – models [4] and [5] for degree centrality, models [7] and [8] for closeness centrality, and [10] and [11] for eigenvector centrality. The results for the network-based centrality measures are consistent with previous studies investigating the relationship between interconnectedness and systemic risk (Cai et al., 2018; Houston et al., 2018).

The recession dummy does not appear as a stand-alone variable in specifications where the interacted terms are employed due multicollinearity concerns. Specifically, as shown in Table 3.5, the correlation levels between the interacted centrality measures and the recession dummy are 79.6% for degree centrality, 98.6% for closeness centrality, and 83.2% for eigenvector centrality. Furthermore, $closeness\ centrality\ x\ US\ Non-Recession$ has a correlation of -86.8% with the U.S. Recession dummy. Indeed, the VIF values of the interacted closeness centrality are well above 10 (Table A. 3.2). We address these concerns by replacing $Centrality\ x\ U.S.Recession$ and $Centrality\ x\ U.S.Non - Recession$ with the residuals of their orthogonalization with the recession dummy. Results are reported in Table A. 3.3 and our main findings are confirmed.[11]

Our results align with the literature for the coefficients associated with the bank's total assets, which are positive and statistically significant, indicating that larger banks are more sensitive to systemic risk (Cai et al., 2018; Laeven et al., 2016; Sedunov, 2016). The coefficient on market size is positive and significant.

[11] We also checked the VIF values of the baseline regression with the orthogonalized variables and none suggests multicollinearity issues. Specifically, the VIF values of the interacted orthogonalized closeness centrality are always below 4 across all model specifications.

Table 3.4: Syndication risk and network centrality as determinants of systemic risk

This table reports estimation results for the panel regression in Equation (7). The dependent variable is ΔSRISK, the monthly change in SRISK, which is the systemic risk indicator proposed by Acharya et al (2017). The explanatory variables are lagged by one-month. They are: the syndication risk measures SN_RISK^{Lev} and $SN\_RISK^{Lev\&CovLite}$ which are defined in Equations (1) and (2); three proxies for network centrality, that is, degree, closeness and eigenvector centrality; the U.S. Recession dummy, based on the USRECD NBER indicator, which is equal to 1 for each month labelled as a recession by the USRECD NBER indicator and zero otherwise. The U.S. non-recession indicator is the complement of the recession dummy. Other control variables included are the lender's total assets (B$), the size of the syndicated loan market (B$), and the one-month lagged SRISK. All regressions include financial institution fixed effects. The sample period includes monthly observations from 2000 to 2022. The bottom of the table reports the number of observations, fixed effects, number of clusters (i.e., financial institutions), and adjusted R-squared values. Lastly, the table reports a number of hypothesis tests and the hypothesis test's p-value. Robust standard errors are clustered at the lender level (in parentheses). * indicates that the estimated coefficient is significantly different from 0 at the 10% level, ** at the 5% level, and *** at the 1% level.

			Degree centrality			Closeness centrality			Eigenvector centrality		
Dependent variable: ΔSRISK	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)	(9)	(10)	(11)
SN_RISK^{Lev} × U.S. Recession	0.699***			0.646***			0.668***			0.582***	
	(0.097)			(0.106)			(0.093)			(0.109)	
SN_RISK^{Lev} × U.S. Non-Recession	0.021			-0.001			0.001			0.038	
	(0.047)			(0.045)			(0.045)			(0.048)	
$SN\_RISK^{Lev\&CovLite}$ × U.S. Recession		0.691***			0.640***			0.660***			0.575***
		(0.093)			(0.102)			(0.090)			(0.105)
$SN\_RISK^{Lev\&CovLite}$ × U.S. Non-Recession		0.005			-0.019			-0.016			0.020
		(0.044)			(0.044)			(0.043)			(0.044)
Centrality × U.S. Recession			0.072***	0.027***	0.027***	0.059***	0.034**	0.035**	0.196***	0.084***	0.084***
			(0.018)	(0.008)	(0.008)	(0.021)	(0.014)	(0.014)	(0.046)	(0.029)	(0.029)
Centrality × U.S. Non-recession			0.011	0.011	0.012*	0.029*	0.025*	0.026*	-0.001	-0.007	-0.005
			(0.007)	(0.007)	(0.007)	(0.015)	(0.013)	(0.014)	(0.008)	(0.009)	(0.009)
U.S. Recession	0.498***	0.486***									
	(0.131)	(0.130)									
Total Assets (B$)	0.002***	0.002***	0.002***	0.003***	0.003***	0.002***	0.003***	0.003***	0.002***	0.002***	0.002***
	(0.000)	(0.000)	(0.000)	(0.000)	(0.000)	(0.000)	(0.000)	(0.000)	(0.000)	(0.000)	(0.000)
Market Size (B$)	0.050***	0.050***	0.047***	0.044**	0.044**	0.047**	0.045**	0.045**	0.055***	0.052***	0.052***
	(0.018)	(0.018)	(0.018)	(0.017)	(0.017)	(0.018)	(0.017)	(0.017)	(0.019)	(0.018)	(0.018)
Lagged SRISK	-0.068***	-0.068***	-0.063***	-0.068***	-0.068***	-0.061***	-0.068***	-0.068***	-0.064***	-0.069***	-0.069***
	(0.013)	(0.013)	(0.013)	(0.013)	(0.013)	(0.012)	(0.013)	(0.013)	(0.013)	(0.013)	(0.013)
Constant	-1.160***	-1.142***	-1.391***	-1.379***	-1.374***	-2.693***	-2.481***	-2.509***	-1.182***	-1.167***	-1.160***
	(0.216)	(0.211)	(0.315)	(0.289)	(0.288)	(0.905)	(0.800)	(0.816)	(0.262)	(0.243)	(0.242)
Observations	11,154	11,154	11,154	11,154	11,154	11,154	11,154	11,154	11,154	11,154	11,154
Financial Institution FE	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes
Clusters	96	96	96	96	96	96	96	96	96	96	96
Adj. R^2	0.054	0.054	0.045	0.054	0.054	0.042	0.054	0.054	0.048	0.055	0.055
H_0: (SN_RISK^{Lev} × Recession - SN_RISK^{Lev} × Non-Recession) = 0	0.678***			0.647***			0.667***			0.544***	
H_0: ($SN\_RISK^{Lev\&CovLite}$ × Recession - $SN\_RISK^{Lev\&CovLite}$ × Non-Recession) = 0		0.686***			0.659***			0.676***			0.555***
H_0: (Centrality *Rec. - Centrality *Non-Rec.) = 0			0.061***	0.016**	0.015**	0.030***	0.009***	0.009***	0.197***	0.091***	0.089***

Table 3.5: Correlation matrix

This table reports the correlation matrix of the main variables of interest employed in the empirical analysis, which are respectively: the ΔSRISK; the U.S. Recession indicator (USRECD) based on the NBER definition; the lender's total assets (B$); the size of the syndicated loan market (B$); the network-based proxies of interconnectedness, which are the Degree, Closeness and Eigenvector centrality measures; and the two measures of syndication risk, SN_RISK^{Lev} and $SN\_RISK^{Lev\&CovLite}$.

	ΔSRISK	U.S. Recession	Total Assets (B$)	Market Size (B$)	Degree Centrality	Degree Centrality × U.S. Recession	Degree Centrality × U.S. Non-Recession	Closeness Centrality	Closeness Centrality × U.S. Recession	Closeness Centrality × U.S. Non-Recession	Eigen Centrality	Eigen Centrality × U.S. Recession	Eigen Centrality × U.S. Non-Recession	SN_RISK^{Lev}	SN_RISK^{Lev} × U.S. Recession	SN_RISK^{Lev} × U.S. Non-Recession	$SN\_RISK^{Lev\&CovLite}$	$SN\_RISK^{Lev\&CovLite}$ × U.S. Recession	$SN\_RISK^{Lev\&CovLite}$ × U.S. Non-Recession
ΔSRISK	1																		
U.S. Recession	0.058	1																	
Total Assets (B$)	0.026	-0.008	1																
Market Size (B$)	0.050	-0.171	-0.014	1															
Degree Centrality	0.022	0.004	0.558	0.026	1														
Degree Centrality × U.S. Recession	0.081	0.796	0.076	-0.134	0.186	1													
Degree Centrality × U.S. Non-Recession	-0.018	-0.380	0.504	0.090	0.880	-0.303	1												
Closeness Centrality	0.023	0.026	0.509	0.043	0.967	0.192	0.845	1											
Closeness Centrality × U.S. Recession	0.066	0.986	0.014	-0.168	0.054	0.884	-0.375	0.075	1										
Closeness Centrality × U.S. Non-Recession	-0.047	-0.868	0.252	0.173	0.455	-0.691	0.775	0.453	-0.855	1									
Eigen Centrality	0.018	0.023	0.607	-0.033	0.924	0.190	0.805	0.893	0.070	0.402	1								
Eigen Centrality × U.S. Recession	0.089	0.832	0.078	-0.156	0.158	0.973	-0.317	0.168	0.905	-0.722	0.190	1							
Eigen Centrality × U.S. Non-Recession	-0.030	-0.418	0.538	0.051	0.799	-0.333	0.936	0.764	-0.412	0.765	0.855	-0.348	1						
SN_RISK^{Lev}	0.022	0.021	0.735	-0.026	0.639	0.153	0.547	0.598	0.057	0.260	0.593	0.134	0.496	1					
SN_RISK^{Lev} × U.S. Recession	0.102	0.457	0.171	-0.092	0.171	0.703	-0.174	0.168	0.541	-0.396	0.172	0.671	-0.191	0.326	1				
SN_RISK^{Lev} × U.S. Non-Recession	-0.020	-0.171	0.704	0.011	0.602	-0.136	0.650	0.560	-0.168	0.441	0.553	-0.142	0.603	0.917	-0.078	1			
$SN\_RISK^{Lev\&CovLite}$	0.020	0.021	0.736	-0.026	0.639	0.152	0.546	0.598	0.057	0.260	0.593	0.134	0.496	0.999	0.325	0.917	1		
$SN\_RISK^{Lev\&CovLite}$ × U.S. Recession	0.102	0.457	0.171	-0.092	0.171	0.704	-0.174	0.168	0.541	-0.397	0.172	0.672	-0.191	0.326	1.000	-0.078	0.325	1	
$SN\_RISK^{Lev\&CovLite}$ × U.S. Non-Recession	-0.022	-0.170	0.704	0.011	0.602	-0.136	0.649	0.560	-0.168	0.441	0.553	-0.142	0.603	0.916	-0.078	0.999	0.918	-0.078	1

3.4.1. Systemically important financial institutions

In this section, we study the extent to which our novel measures of syndicated loan risk are useful determinants of changes in the systemic risk variation when SIFIs are considered separately from other financial institutions. This is motivated by the fact that, as indicated by our network analysis and SN_RISK statistics, the actions and risk-taking of SIFIs can have a greater impact on the overall financial system compared to non-systemically relevant institutions. For this purpose, we first re-run the main regressions segmented according to the systemic importance of the lender. Our findings are reported in Table 3.6. Panel A indicates that, for SIFIs, both the coefficients $SN\_RISK_{i,t-1}^{Lev}$ and $SN\_RISK_{i,t-1}^{Lev\&CovLite}$, when interacted with the recession dummy, are positive and statistically significant across all the model specifications, as in the main regressions. An increase of one standard deviation in a systemically important bank's market share of highly risky loans during a period of recession is both statistically and economically significant. The estimated increase in the mean $SRISK$ variation is around 28% to 35% when the US economy has been in a recession for at least six months. Similarly, the results for centrality confirm the positive relationship between systemic risk and network centrality during periods of recession. The result is economically significant, as an increase of one standard deviation in centrality during a recession lasting at least six months results in a 16% to 27% rise of systemic risk.

By contrast, Panel B indicates that for non-systemically important institutions, the statistical significance of $SN\_RISK_{i,t-1}^{Lev}$ and $SN\_RISK_{i,t-1}^{Lev\&CovLite}$ is not robust across different specifications. In particular, statistical significance disappears when degree and eigenvector centrality are used. This is probably due to the facts that systemic risk is low for this subset of financial institutions and that their presence in the market of leveraged and covenant-lite loans is small. Nevertheless, centrality interacted with recession is still statistically significant, which suggests that network interconnectedness remains an important determinant of the systemic risk variations for less systemic lenders. Our findings support the relevance of interconnectedness as a potential source of systemic risk across the entire syndicated loan market.

Table 3.6: SIFIs and non SIFIs

This table reports estimation results for the panel regression in Equation (7) for systemically important financial institutions (Panel A) and other financial institutions (Panel B). The dependent variable is ΔSRISK, the monthly change in SRISK, which is the systemic risk indicator proposed by Acharya et al (2017). The explanatory variables are lagged by one-month. They are: the syndication risk measures SN_RISK^{Lev} and $SN\_RISK^{Lev\&CovLite}$ which are defined in Equations (1) and (2); three proxies for network centrality, that is, degree, closeness and eigenvector centrality; the U.S. Recession dummy, based on the USRECD NBER indicator, which is equal to 1 for each month labelled as a recession by the USRECD NBER indicator and zero otherwise. The U.S. non-recession indicator is the complement of the recession dummy. Other control variables included are the lender's total assets (B$), the size of the syndicated loan market (B$), and the one-month lagged SRISK. All regressions include financial institution fixed effects. The bottom of the table reports the number of observations, fixed effects, number of clusters (i.e., financial institutions), and adjusted R-squared. Lastly, the table reports a number of hypothesis tests and the hypothesis test's p-value. Robust standard errors are clustered at the lender level (in parentheses). * indicates that the estimated coefficient is significantly different from 0 at the 10% level, ** at the 5% level, and *** at the 1% level.

Panel A. Systemically important financial institutions (SIFIs)

			Degree centrality			Closeness centrality			Eigenvector centrality		
Dependent variable: ΔSRISK	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)	(9)	(10)	(11)
SN_RISK^{Lev} × U.S. Recession	0.708***			0.660***			0.670***			0.566***	
	(0.110)			(0.125)			(0.105)			(0.135)	
SN_RISK^{Lev} × U.S. Non-Recession	0.034			0.003			0.001			0.049	
	(0.054)			(0.050)			(0.050)			(0.056)	
$SN\_RISK^{Lev\&CovLite}$ × U.S. Recession		0.700***			0.654***			0.661***			0.558***
		(0.106)			(0.121)			(0.101)			(0.131)
$SN\_RISK^{Lev\&CovLite}$ × U.S. Non-Recession		0.015			-0.017			-0.019			0.029
		(0.050)			(0.049)			(0.049)			(0.052)
Centrality × U.S. Recession			0.089***	0.035**	0.035**	0.092**	0.057*	0.058*	0.252***	0.119**	0.120**
			(0.024)	(0.013)	(0.013)	(0.037)	(0.028)	(0.028)	(0.061)	(0.051)	(0.051)
Centrality × U.S. Non-recession			0.015	0.016	0.017	0.050*	0.044	0.046	0.009	0.001	0.003
			(0.011)	(0.011)	(0.012)	(0.028)	(0.027)	(0.027)	(0.016)	(0.018)	(0.018)
U.S. Recession	0.744**	0.721**									
	(0.274)	(0.272)									
Total Assets (B$)	0.003***	0.003***	0.003***	0.003***	0.003***	0.003***	0.003***	0.003***	0.002***	0.003***	0.003***
	(0.000)	(0.000)	(0.000)	(0.000)	(0.000)	(0.000)	(0.000)	(0.000)	(0.000)	(0.000)	(0.000)
Market Size (B$)	0.087**	0.087**	0.082**	0.078**	0.078**	0.081**	0.078**	0.077**	0.097**	0.091**	0.091**
	(0.035)	(0.035)	(0.034)	(0.033)	(0.033)	(0.034)	(0.034)	(0.034)	(0.037)	(0.036)	(0.036)
Lagged SRISK	-0.068***	-0.068***	-0.062***	-0.067***	-0.067***	-0.061***	-0.068***	-0.068***	-0.064***	-0.068***	-0.068***
	(0.013)	(0.013)	(0.013)	(0.014)	(0.014)	(0.013)	(0.014)	(0.014)	(0.013)	(0.014)	(0.014)
Constant	-2.032***	-1.999***	-2.484***	-2.500***	-2.493***	-4.892**	-4.612**	-4.666**	-2.158***	-2.143***	-2.136***
	(0.390)	(0.380)	(0.618)	(0.573)	(0.572)	(1.844)	(1.692)	(1.723)	(0.544)	(0.512)	(0.511)
Observations	5,279	5,279	5,279	5,279	5,279	5,279	5,279	5,279	5,279	5,279	5,279
Financial Institution FE	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes
Clusters	26	26	26	26	26	26	26	26	26	26	26
Adj. R^2	0.056	0.056	0.048	0.056	0.056	0.045	0.057	0.057	0.051	0.058	0.057
H_0:(SN_RISK^{Lev} × Recession - SN_RISK^{Lev} × Non-Recession) = 0	0.674***			0.657***			0.669***			0.517***	
H_0:($SN\_RISK^{Lev\&CovLite}$ × Recession - $SN\_RISK^{Lev\&CovLite}$ × Non-Recession) = 0		0.685***			0.671***			0.680***			0.529***
H_0:(Centrality *Rec. - Centrality *Non-Rec.) = 0			0.074***	0.019*	0.018*	0.042***	0.013**	0.012**	0.243***	0.118**	0.117**

Panel B. Non systemically important financial institutions (non SIFIs)

			Degree centrality			Closeness centrality			Eigenvector centrality		
Dependent variable: ΔSRISK	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)	(9)	(10)	(11)
SN_RISK^{Lev} × U.S. Recession	0.282***			0.123			0.231**			0.083	
	(0.078)			(0.118)			(0.090)			(0.124)	
SN_RISK^{Lev} × U.S. Non-Recession	-0.021			-0.026			-0.026			-0.000	
	(0.039)			(0.035)			(0.039)			(0.028)	
$SN\_RISK^{Lev\&CovLite}$ × U.S. Recession		0.284***			0.127			0.233**			0.088
		(0.077)			(0.116)			(0.088)			(0.122)
$SN\_RISK^{Lev\&CovLite}$ × U.S. Non-Recession		-0.026			-0.031			-0.032			-0.006
		(0.041)			(0.038)			(0.041)			(0.031)
Centrality × U.S. Recession			0.031***	0.027***	0.027***	0.018***	0.016***	0.016***	0.082***	0.075***	0.075***
			(0.005)	(0.007)	(0.007)	(0.005)	(0.005)	(0.005)	(0.012)	(0.016)	(0.016)
Centrality × U.S. Non-recession			0.003	0.004	0.004	0.006	0.007*	0.007*	-0.004	-0.004	-0.004
			(0.003)	(0.003)	(0.003)	(0.004)	(0.004)	(0.004)	(0.010)	(0.009)	(0.009)
U.S. Recession	0.444***	0.441***									
	(0.119)	(0.118)									
Total Assets (B$)	0.003***	0.003***	0.003***	0.003***	0.003***	0.003***	0.003***	0.003***	0.003***	0.003***	0.003***
	(0.001)	(0.001)	(0.001)	(0.001)	(0.001)	(0.001)	(0.001)	(0.001)	(0.001)	(0.001)	(0.001)
Market Size (B$)	0.008	0.008	0.005	0.005	0.005	0.007	0.007	0.007	0.007	0.007	0.007
	(0.005)	(0.005)	(0.005)	(0.005)	(0.005)	(0.005)	(0.005)	(0.005)	(0.005)	(0.005)	(0.005)
Lagged SRISK	-0.095***	-0.095***	-0.097***	-0.096***	-0.096***	-0.095***	-0.096***	-0.096***	-0.098***	-0.098***	-0.098***
	(0.020)	(0.020)	(0.020)	(0.020)	(0.020)	(0.020)	(0.020)	(0.020)	(0.021)	(0.021)	(0.021)
Constant	-0.383***	-0.381***	-0.415***	-0.413***	-0.412***	-0.700***	-0.706***	-0.710***	-0.370***	-0.371***	-0.370***
	(0.077)	(0.077)	(0.104)	(0.100)	(0.100)	(0.245)	(0.244)	(0.244)	(0.088)	(0.086)	(0.086)
Observations	5,875	5,875	5,875	5,875	5,875	5,875	5,875	5,875	5,875	5,875	5,875
Financial Institution FE	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes
Clusters	72	72	72	72	72	72	72	72	72	72	72
Adj. R^2	0.055	0.055	0.055	0.055	0.055	0.054	0.055	0.055	0.057	0.057	0.057
H_0:(SN_RISK^{Lev} × Recession - SN_RISK^{Lev} × Non-Recession) = 0	0.303**			0.149			0.257**			0.083	
H_0:($SN\_RISK^{Lev\&CovLite}$ × Recession - $SN\_RISK^{Lev\&CovLite}$ × Non-Recession) = 0		0.310**			0.158			0.265**			0.094
H_0:(Centrality *Rec. - Centrality *Non-Rec.) = 0			0.028***	0.023***	0.023***	0.012***	0.009***	0.009***	0.086***	0.079***	0.079***

3.4.2. Robustness

In this section, to complement the main analysis, we perform the following robustness tests. Given that larger banks tend to have higher systemic risk (Cai et al., 2018; Laeven et al., 2016; Sedunov, 2016), a possible concern might be that the relationship between the syndication risk measures and systemic risk is driven by bank size. As can be seen in Table 3.5, this concern might arise because the SN_RISK variable interacted with the non-recession dummy shows a correlation greater than 70% with total assets. To address this potential issue, we orthogonalize the SN_RISK measures with respect to total assets. We report the results in Table A. 3.4. The sign and significance of SN_RISK x $U.S. Recession$ are in line with previous findings, even though significance is weaker (now at the 5% or 10% level). Furthermore, SN_RISK interacted with $U.S. Non - Recession$ is now also positive and significant but not consistently so across all specifications. This suggests that exposure to leveraged and covenant lite loan syndication might increase systemic risk also in normal economic conditions.

To ensure the observed effects stem from the core explanatory variables rather than other time-dependent factors, we control for time fixed effects and utilize time-level clustered robust standard errors. The results are reported in Table A. 3.5 in the Appendix, and they confirm that the previous findings are robust and not driven by other time-dependent factors.

The centrality measures employed in our main analysis are obtained from network-based connections among lenders in the syndicated loans market. However, Cai et al. (2018) propose an alternative method, which looks at the Euclidean distance among lenders' portfolios.[12] We conduct a robustness test by replacing the network-based centrality measures

[12] Cai et al. (2018) defines the monthly Euclidean portfolio distance between two lenders i and k as follows:

$$Distance_{i,k,t} = \frac{1}{\sqrt{2}} * \sqrt{\sum_{j=1}^{J} \left(w_{i,j,t} - w_{k,j,t}\right)^2}, \tag{8}$$

with the interconnectedness based on the Euclidean portfolio distance. However, while the latter considers the similarity or dissimilarity between two lenders' portfolios based on the industries (or U.S. states) in which they have invested, the network analysis provides insights into the relationships between lenders and allow us to identify which lenders are more influential in the syndicated network, and hence more likely to contribute to systemic risk. Differently from Cai et al. (2018), we incorporate the decline in the share detected in the syndicated market after origination by employing a 1-month horizon (Blickle et al., 2020), instead of a 12-month rolling sum, to calculate interconnectedness based on the Euclidean distance. The results are reported in Table A. 3.6. Again, SN_RISK interacted with the recession dummy is positive and statistically significant across all model specifications. The significance of interconnectedness

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where $w_{i,j,t}$ is a weight that captures the amount invested by lender i in "specialisation" j in month t. As a robustness test, we consider the specialisation by industry of amount allocation. Specifically, we consider the industrial sector to which the borrower belongs (i.e., manufacturing, oil and gas, etc.). Intuitively, a distance equal to 0 between lenders i and k indicates that their loan portfolios are identical. This occurs when lender i lends to borrowers in the same industrial sector or location as those receiving loans from lender k. On the other hand, a distance of 1 signifies a complete difference between the two portfolios, meaning that lenders i and k issue loans to borrowers in different industrial sectors or locations. Second, we use the measure of portfolios distance to compute the interconnectedness of lender i in month t, which is defined as

$$Interconnectedness_{i,t} = (1 - \sum_{k \neq 1} x_{i,k,t} * Distance_{i,k,t}) * 100 \tag{9}$$

As in Cai et al. (2018) we apply the three alternative weighting schemes $x_{i,k,t}$ in which each financial institution in the sample is equally weighted, (2) institutions are size-weighted, or (3) weights reflect the number of lending relationships an institution has in the market.

interacted with recession is also robust across the weighting schemes applied to derive the interconnectedness measures.

In the main analysis, the centrality measures are calculated based on the entire syndicated loan market, rather than just the leveraged and covenant-lite market segment. However, we also conducted additional tests by limiting the network analysis to the leveraged and covenant-lite market segment. The results of these tests are presented in Table A. 3.7 and show that our findings remain robust also when focusing solely on the leveraged and covenant-lite segments of the syndicated market.

To account for the potential impact of regulatory metrics on systemic risk, we include Risk Adjusted Capital TIER1, Risk Adjusted Capital TIER2, and loan loss provisions as control variables in some of our models. However, due to their limited availability across the banks in our sample, we did not include these metrics in every model. The results, reported in Table A. 3.8, shows that our main findings remain robust. The coefficient of loan loss provisions is positive and statistically significant, indicating that an increase in provisions is associated with an increase in systemic risk. This may be due to higher levels of loan defaults and credit losses, which can increase the likelihood of distress among lenders and contagion across the financial system.

In light of Berlin et al.'s (2020) finding that lenders maintain control rights by specifying covenants on the revolvers within a loan package for risky borrowers, we refine the definition of covenant-lite loans to exclude those that contain any covenants across all facilities in a package. The results are reported in Table A. 3.9 and demonstrate that our previous findings remain unchanged. One potential issue with our analysis is the assumption that all loans are equally risky. To address this concern, we enhanced our main measure of syndication risk in two ways. Firstly, we refine the definition of leveraged loans to include only those that are highly leveraged, and then consider only the leveraged loans that are not highly leveraged. This allows us to examine whether the lender’s market share in one of these two specific segments explains systemic risk variations. However, our results reported in Table A. 3.10 indicate that regardless of whether the leveraged loans are highly leveraged or not, the lender's market share in this segment remains a significant explanatory variable for systemic risk variations.

Secondly, we include information on loan spreads as a continuous metric to reflect the risk level of borrowers. To redefine our measure of syndication risk, we weight each tranche amount by its corresponding Libor spread. This measure can be interpreted such that a higher value indicates a larger share of high-spread loans held by a lender in the market. Therefore, a higher value of $SN\_RISK^{SpreadWeigh}$, implies a greater contribution of that lender to lending high-spread loans. Table A. 3.11 reports the results, which are in line with our main conclusions.

To employ an alternative measure of systemic risk, we replace our main dependent variable with $\Delta LRMES$ (Brownlees and Engle, 2017). Table A. 3.12 indicates that the main conclusions about SN_RISK, when interacted with the recession dummy, remain robust across all model specifications. We also test an alternative regression model with only one dummy business cycle dummy, U.S. Recession, and the variables of interest as stand-alone as well as interacted with "U.S. Recession". The results shown in Table A. 3.13 mirror our previous conclusions in that it is only during periods of recession that we consistently detect a positive and significant impact of SN_RISK and centrality measures on systemic risk.

The main analysis in this study uses a dummy variable to identify three separate recession periods. The longest of these corresponds to the Great Financial Crisis. One may question whether our core results are driven solely by such crisis. To address this, we break down the recession periods into three distinct dummy variables: "Recession period 1", which spans from April to November 2001; "Recession period 2", which spans from January 2008 to June 2009; and "Recession period 3", which spans from March to April 2020. The results of this alternative regression analysis are reported in Table A. 3.14 and show that the core findings are confirmed for the Great Financial Crisis and the COVID recession. By contrast, Recession period 1 is not significant. The size of the coefficients and significance of the recession dummies, both when stand alone and interacted, suggest that it is the severity of the recession that determines the importance of its impact on systemic risk, as one may expect. Indeed, the COVID recession has the largest coefficients as it was associated with the biggest contraction in real GDP (-19.2%), followed by the Great Financial Crisis (-5.1%) and the early 2000s recession (-0.3%).[13]

[13] See for reference the https://www.nber.org/research/business-cycle-dating

3.5. Conclusions

In this paper, we study the U.S. syndicated loans market and, specifically, its leveraged and covenant-lite segments. Since the Great Recession, the proportion of leveraged loans has remained high, at around 40% of the overall market. We investigate the network topology of the market, and its historical evolution indicates a leading role of systemically important financial institutions, which are the key sources of interconnectedness in loan syndications. We calculate measures of network centrality, which we use as proxies of interconnectedness, to explain systemic risk variations at the level of individual lenders. Our empirical analysis reveals that these measures explain systemic risk variations, especially during periods of recession.

To determine whether there is any relationship between loan syndication and systemic risk, we develop SN_RISK, a measure of risk for syndicated loan portfolios. SN_RISK reflects the proportion of leveraged and covenant-lite loans held by a financial institution relative to the syndication market. We focus on these specific market segments of leveraged loans and covenant-lite loans, as these types of loans could lead to pipeline risk. This means that these loans could become less marketable during periods of recession and impair the ability of the owner to offload them to other investors. We find that SN_RISK can help explain the systemic risk of lenders over different model specifications and a battery of robustness tests.

Our findings show that banks with a higher market share of risky loans are more vulnerable to losses during a crisis, which could lead to contagion effects and amplify systemic risk. This new measure would be a valuable addition to the toolkit used by regulators and policymakers to assess and rank systemically important institutions both domestically and globally.

APPENDIX TO CHAPTER 3

Appendix A. Thomson Reuters criteria to identify leveraged loans. Here, we provide the leveraged loan definition reported in Global Syndicated Loans League Table Criteria (2018) by Thomson Reuters. "Deals will be identified as leveraged and included in leveraged loan league tables based on a combination of the following criteria:

- Margins: Transactions with a drawn spread of at least LIBOR+175 bps (basis points) for US. syndications.
- Ratings: Transactions for issuers with senior debt ratings of BB+/Ba1 or lower. In the event of a split rating, the higher rating will apply.
- Private equity sponsor-backed financings: Transactions whereby a private equity sponsor maintains an ownership position allowing them to influence the management of the company via buyouts or leveraging of issuer.
- Loans to unrated companies will be included in the leveraged loan league tables on a case-by-case basis as long as the spread is greater than or equal to the applicable LIBOR margin thresholds. In case the pricing does not represent market characteristics, debt- to-EBITDA levels may be considered on a case-by-case basis for unrated issuers.
- For U.S. leveraged deals structured with an asset-based component with spreads less than the applicable LIBOR margin thresholds, the entire deal would continue to receive leveraged league table credit.

The following types of loans are excluded from the leveraged league table regardless of pricing and borrower rating: traditional project finance, real estate, and securitization projects.

Thomson Reuters will take a holistic view to determine whether a deal should be tracked in the investment grade, leveraged, or highly leveraged league tables and will look at a series of variables including ratings, pricing, debt ratios, and sponsor involvement to accurately determine appropriate accreditation."

Table A. 3.1: DealScan syndicated loans database: variables selection

This table describes the main variables extracted from the DealScan syndicated loans database and employed in the analysis.

Group	#	Variables
Borrowers details	V1	Borrower name and unique identifier
	V2	State where the borrower is headquartered
	V3	Country and region of headquarter
	V4	Primary Standard Industrial Classification Code to which the borrower belongs
Loans details	V5	Deal and tranche unique identifier
	V6	Tranche origination or amended
	V7	Tranche active date
	V8	Tranche market segment (Investment grade, leveraged, covenant-lite, etc.)
	V9	Tranche covenants
	V10	Tranche market of syndication
	V11	Distribution method (restricted to syndication)
	V12	Tranche type (i.e. term loan A, term loan B, other loan, etc.)
	V13	Tranche currency
	V14	Tranche amount converted in millions of USD
	V15	Tranche base rate & margin (bps)
Lenders details	V16	Lender parent name and unique identifier
	V17	Lender name and unique identifier
	V18	Primary Role (i.e. syndication agent, admin agent, participant, etc.)
	V19	Lender Share (%)

Table A. 3.2: VIF values of regression model presented in table 3.4 (Syndication risk and network centrality as determinants of systemic risk)

This table reports the VIF (Variance Inflation Factor) values of the main regression model presented in Table 3.4. The dependent variable is ΔSRISK, the monthly change in SRISK, which is the systemic risk indicator proposed by Acharya et al (2017). The explanatory variables are lagged by one-month. They are: the syndication risk measures SN_RISK^{Lev} and $SN\_RISK^{Lev\&CovLite}$ which are defined in Equations (1) and (2); three proxies for network centrality, that is, degree, closeness and eigenvector centrality; the U.S. Recession dummy, based on the USRECD NBER indicator, which is equal to 1 for each month labelled as a recession by the USRECD NBER indicator and zero otherwise. The U.S. non-recession indicator is the complement of the recession dummy. Other control variables included are the lender's total assets (B$), the size of the syndicated loan market (B$), and the one-month lagged SRISK. All regressions include financial institution fixed effects. The sample period includes monthly observations from 2000 to 2022. The bottom of the table reports the number of observations, fixed effects, number of clusters (i.e., financial institutions).

			Degree centrality			Closeness centrality			Eigenvector centrality		
Dependent variable: ΔSRISK	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)	(9)	(10)	(11)
SN_RISK^{Lev} × U.S. Recession	1.68			2.33			1.83			2.18	
SN_RISK^{Lev} × U.S. Non-Recession	3.88			4.21			4.08			4.09	
$SN\_RISK^{Lev\&CovLite}$ × U.S. Recession		1.68			2.34			1.83			2.19
$SN\_RISK^{Lev\&CovLite}$ × U.S. Non-Recession		3.89			4.22			4.08			4.10
Centrality × U.S. Recession			2.24	3.21	3.21	13.86	14.82	14.82	2.39	3.23	3.24
Centrality × U.S. Non-recession			4.98	5.37	5.36	15.63	16.39	16.39	5.29	5.54	5.54
U.S. Recession	1.36	1.36									
Total Assets (B$)	6.31	6.31	6.24	6.43	6.43	6.27	6.54	6.53	6.46	6.56	6.56
Market Size (B$)	1.05	1.05	1.06	1.06	1.06	1.07	1.08	1.08	1.05	1.05	1.05
Lagged SRISK	2.40	2.40	2.34	2.40	2.40	2.32	2.40	2.40	2.35	2.41	2.41
Observations	11,154	11,154	11,154	11,154	11,154	11,154	11,154	11,154	11,154	11,154	11,154
Financial Institution FE	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes
Clusters	96	96	96	96	96	96	96	96	96	96	96

Table A. 3.3: Orthogonalisation of centrality

This table reports estimation results for the panel regression in Equation (7). The dependent variable is ΔSRISK, the monthly change in SRISK, which is the systemic risk indicator proposed by Acharya et al (2017). The explanatory variables are lagged by one-month. They are: the syndication risk measures SN_RISK^{Lev} and $SN\_RISK^{Lev\&CovLite}$ which are defined in Equations (1) and (2); three proxies for network centrality, that is, degree, closeness and eigenvector centrality; the U.S. Recession dummy, based on the USRECD NBER indicator, which is equal to 1 for each month labelled as a recession by the USRECD NBER indicator and zero otherwise. The U.S. non-recession indicator is the complement of the recession dummy. Differently from the main analysis, we replace the Centrality×U.S. Recession and Centrality×U.S. Non-Recession with the residuals of their orthogonalisation with the recession dummy. Other control variables included are the lender's total assets (B$), the size of the syndicated loan market (B$), and the one-month lagged SRISK. All regressions include financial institution fixed effects. The sample period includes monthly observations from 2000 to 2022. The bottom of the table reports the number of

	Degree centrality			Closeness centrality			Eigenvector centrality		
Dependent variable: ΔSRISK	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)	(9)
SN_RISK^{Lev} × U.S. Recession		0.704***			0.711***			0.678***	
		(0.105)			(0.097)			(0.110)	
SN_RISK^{Lev} × U.S. Non-Recession		0.006			0.005			0.030	
		(0.053)			(0.052)			(0.053)	
$SN\_RISK^{Lev\&CovLite}$ × U.S. Recession			0.696***			0.703***			0.670***
			(0.101)			(0.093)			(0.105)
$SN\_RISK^{Lev\&CovLite}$ × U.S. Non-Recession			-0.011			-0.012			0.012
			(0.054)			(0.052)			(0.052)
Centrality × U.S. Recession (Orth.)	0.051***	0.025**	0.025**	0.048***	0.041***	0.042***	0.234***	0.155***	0.156***
	(0.010)	(0.011)	(0.010)	(0.013)	(0.013)	(0.013)	(0.053)	(0.052)	(0.052)
Centrality × U.S. Non-Recession (Orth.)	0.009	0.009	0.009	0.023**	0.021*	0.022*	-0.009	-0.019**	-0.018**
	(0.006)	(0.007)	(0.007)	(0.011)	(0.013)	(0.013)	(0.006)	(0.009)	(0.008)
U.S. Recession	1.304***	0.428***	0.417***	1.237***	0.270***	0.258***	1.075***	0.261***	0.249***
	(0.372)	(0.109)	(0.107)	(0.370)	(0.092)	(0.091)	(0.300)	(0.080)	(0.079)
Total Assets (B$)	0.002***	0.003***	0.003***	0.003***	0.003***	0.003***	0.002***	0.003***	0.003***
	(0.000)	(0.000)	(0.000)	(0.000)	(0.000)	(0.000)	(0.000)	(0.000)	(0.000)
Constant	-1.129***	-1.227***	-1.207***	-1.117***	-1.204***	-1.185***	-1.118***	-1.244***	-1.225***
	(0.221)	(0.228)	(0.223)	(0.218)	(0.223)	(0.218)	(0.215)	(0.223)	(0.218)
Control variables	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes
Observations	10,212	10,212	10,212	10,212	10,212	10,212	10,212	10,212	10,212
Financial Institution FE	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes
Clusters	93	93	93	93	93	93	93	93	93
Adj. R^2	0.050	0.065	0.065	0.049	0.066	0.066	0.054	0.068	0.068

Table A. 3.4: Orthogonalisation of $SN-RISK^{Lev}$ and $SN-RISK^{Lev\&CovLite}$

This table reports estimation results for the panel regression in Equation (7). The dependent variable is ΔSRISK, the monthly change in SRISK, which is the systemic risk indicator proposed by Acharya et al (2017). The explanatory variables are lagged by one-month. Differently from the main analysis, we replace the SN_RISK^{Lev} and $SN\_RISK^{Lev\&CovLite}$ variables with the residuals of their orthogonalisation with the total assets variable, interacted by the US Recession and US Non-Recession dummies. We also include three proxies for network centrality, that is, degree, closeness and eigenvector centrality. The U.S. Recession dummy is based on the USRECD NBER indicator, which is equal to 1 for each month labelled as a recession by the USRECD NBER indicator and zero otherwise. The U.S. non-recession indicator is the complement of the recession dummy. Other control variables included are the lender's total assets (B$), the size of the syndicated loan market (B$), and the one-month lagged SRISK. All regressions include financial institution fixed effects. The sample period includes monthly observations from 2000 to 2022. The bottom of the table reports the number of observations, fixed effects, number of clusters (i.e., financial institutions), and adjusted R-squared values. Robust standard errors are clustered at the lender level (in parentheses).

			Degree centrality		Closeness centrality		Eigenvector centrality	
Dependent variable: ΔSRISK	(1)	(2)	(3)	(4)	(6)	(7)	(7)	(8)
SN_RISK^{Lev} × U.S. Recession (Orth.)	0.549**		0.401*		0.503**		0.410*	
	(0.243)		(0.213)		(0.230)		(0.215)	
SN_RISK^{Lev} × U.S. Non-Recession (Orth.)	0.095**		0.077*		0.075*		0.100**	
	(0.042)		(0.042)		(0.041)		(0.045)	
$SN\_RISK^{Lev\&CovLite}$ × U.S. Recession (Orth.)		0.546**		0.395*		0.499**		0.405*
		(0.238)		(0.207)		(0.225)		(0.210)
$SN\_RISK^{Lev\&CovLite}$ × U.S. Non-Recession (Orth.)		0.074*		0.055		0.053		0.078*
		(0.040)		(0.041)		(0.040)		(0.042)
Centrality × U.S. Recession			0.067***	0.067***	0.052***	0.053***	0.180***	0.181***
			(0.017)	(0.017)	(0.019)	(0.020)	(0.042)	(0.043)
Centrality × U.S. Non-Recession			0.007	0.008	0.023*	0.023*	-0.013	-0.012
			(0.006)	(0.007)	(0.013)	(0.014)	(0.009)	(0.009)
U.S. Recession	1.506***	1.507***						
	(0.362)	(0.362)						
Total Assets (B$)	0.002***	0.002***	0.002***	0.002***	0.002***	0.002***	0.002***	0.002***
	(0.000)	(0.000)	(0.000)	(0.000)	(0.000)	(0.000)	(0.000)	(0.000)
Constant	-1.054***	-1.059***	-1.274***	-1.292***	-2.325***	-2.377***	-1.054***	-1.069***
	(0.211)	(0.212)	(0.295)	(0.303)	(0.822)	(0.848)	(0.253)	(0.256)
Control variables	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes
Observations	11,154	11,154	11,154	11,154	11,154	11,154	11,154	11,154
Financial Institution FE	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes
Clusters	96	96	96	96	96	96	96	96
Adj. R^2	0.042	0.042	0.047	0.047	0.044	0.044	0.050	0.050

Table A. 3.5: Syndication risk and network centrality as determinants of systemic risk - year fixed effects

This table reports estimation results for the panel regression in Equation (7). The dependent variable is ΔSRISK, the monthly change in SRISK, which is the systemic risk indicator proposed by (2017). The explanatory variables are lagged by one-month. They are: the syndication risk measures SN_RISK^{Lev} and SN_RISK$^{Lev\&CovLite}$ which are defined in Equations (1) and (2); three proxie centrality, that is, degree, closeness and eigenvector centrality; the U.S. Recession dummy, based on the USRECD NBER indicator, which is equal to 1 for each month labelled as a recession by NBER indicator and zero otherwise. The U.S. non-recession indicator is the complement of the recession dummy. Other control variables included are the lender's total assets (B$), the size of t loan market (B$), and the one-month lagged SRISK. Differently from the main analysis, all regressions include both year and financial institution fixed effects. Also, robust standard errors are c year and lender level (in parentheses). The sample period includes monthly observations from 2000 to 2022. The bottom of the table reports the number of observations, fixed effects, number of financial institutions), and adjusted R-squared values. * indicates that the estimated coefficient is significantly different from 0 at the 10% level, ** at the 5% level, and *** at the 1% level.

			Degree centrality			Closeness centrality			Eigenvector centra	
Dependent variable: ΔSRISK	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)	(9)	(10)
SN_RISK^{Lev} × U.S. Recession	0.708***			0.650***			0.671***			0.573***
	(0.143)			(0.165)			(0.147)			(0.151)
SN_RISK^{Lev} × U.S. Non-Recession	0.019			0.012			0.010			0.040
	(0.074)			(0.078)			(0.076)			(0.076)
SN_RISK$^{Lev\&CovLite}$ × U.S. Recession		0.701***			0.645***			0.664***		
		(0.143)			(0.165)			(0.146)		
SN_RISK$^{Lev\&CovLite}$ × U.S. Non-Recession		0.002			-0.006			-0.007		
		(0.076)			(0.080)			(0.078)		
U.S. Recession	0.832***	0.822***								
	(0.302)	(0.300)								
Centrality × U.S. Recession			0.076***	0.024**	0.023**	0.063***	0.028***	0.029***	0.233***	0.108***
			(0.013)	(0.010)	(0.010)	(0.011)	(0.010)	(0.010)	(0.045)	(0.033)
Centrality × U.S. Non-recession			0.004	0.005	0.005	0.019**	0.013	0.014	-0.017*	-0.018
			(0.005)	(0.005)	(0.005)	(0.008)	(0.008)	(0.009)	(0.010)	(0.012)
Total Assets (B$)	0.002***	0.002***	0.002***	0.002***	0.002***	0.002***	0.002***	0.002***	0.002***	0.002***
	(0.000)	(0.000)	(0.000)	(0.000)	(0.000)	(0.000)	(0.000)	(0.000)	(0.000)	(0.000)
Constant	-2.884***	-2.884***	-2.740***	-2.937***	-2.942***	-3.534***	-3.472***	-3.520***	-2.701***	-2.844***
	(0.821)	(0.821)	(0.814)	(0.816)	(0.816)	(0.895)	(0.891)	(0.896)	(0.815)	(0.821)
Control Variables	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes
Observations	11,154	11,154	11,154	11,154	11,154	11,154	11,154	11,154	11,154	11,154
Financial Institution FE	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes
Year FE	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes
Clusters	118	118	118	118	118	118	118	118	118	118
Adj. R^2	0.064	0.064	0.056	0.064	0.064	0.052	0.064	0.064	0.059	0.066

Table A. 3.6: Syndication risk and interconnectedness as determinants of systemic risk – Cai et al. (2018) alternative interconnectedness

This table reports estimation results for the panel regression in Equation (7). The dependent variable is ΔSRISK, the monthly change in SRISK, which is the systemic risk indicator proposed by Acharya et al (2017). The explanatory variables are lagged by one-month. They are: the syndication risk measures SN_RISK^{Lev} and $SN\_RISK^{Lev\&CovLite}$ which are defined in Equations (1) and (2); the equally-weighted, size-weighted, and relationship-weighted interconnectedness, which are based on Cai et al. (2018) methodology; the U.S. Recession dummy, based on the USRECD NBER indicator, which is equal to 1 for each month labelled as a recession by the USRECD NBER indicator and zero otherwise. The U.S. non-recession indicator is the complement of the recession dummy. Other control variables included are the lender's total assets (B$), the size of the syndicated loan market (B$), and the one-month lagged SRISK. All regressions include financial institution fixed effects. The sample period includes monthly observations from 2000 to 2022. The bottom of the table reports the number of observations, fixed effects, number of clusters (i.e., financial institutions), and adjusted R-squared values. Robust standard errors are clustered at the lender level (in parentheses).

	Equally-weighted (E-W) interconnectedness			Size-weighted (S-W) interconnectedness			Relationship-weighted (REL-W) interconnectedness		
Dependent variable: ΔSRISK	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)	(9)
SN_RISK^{Lev} × U.S. Recession		0.708***			0.700***			0.695***	
		(0.098)			(0.098)			(0.098)	
SN_RISK^{Lev} × U.S. Non-Recession		0.022			0.020			0.020	
		(0.047)			(0.047)			(0.047)	
$SN\_RISK^{Lev\&CovLite}$ × U.S. Recession			0.701***			0.693***			0.687***
			(0.094)			(0.094)			(0.094)
$SN\_RISK^{Lev\&CovLite}$ × U.S. Non-Recession			0.006			0.004			0.004
			(0.044)			(0.044)			(0.044)
Interconnectedness × U.S. Recession	0.025***	0.013***	0.012***	0.032***	0.023***	0.023***	0.025***	0.010***	0.010***
	(0.007)	(0.005)	(0.005)	(0.009)	(0.007)	(0.007)	(0.006)	(0.003)	(0.003)
Interconnectedness × U.S. Non-recession	0.002	0.005	0.005	0.012**	0.016***	0.016***	0.002	0.003	0.003
	(0.003)	(0.004)	(0.004)	(0.005)	(0.006)	(0.006)	(0.002)	(0.002)	(0.002)
Total Assets (B$)	0.002***	0.002***	0.002***	0.002***	0.002***	0.002***	0.002***	0.002***	0.002***
	(0.000)	(0.000)	(0.000)	(0.000)	(0.000)	(0.000)	(0.000)	(0.000)	(0.000)
Constant	-1.174***	-1.491***	-1.458***	-2.009***	-2.386***	-2.373***	-1.221***	-1.356***	-1.345***
	(0.287)	(0.365)	(0.353)	(0.519)	(0.600)	(0.596)	(0.237)	(0.256)	(0.253)
Control variables	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes
Observations	11,154	11,154	11,154	11,154	11,154	11,154	11,154	11,154	11,154
Financial Institution FE	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes
Clusters	96	96	96	96	96	96	96	96	96
Adj. R^2	0.038	0.054	0.054	0.039	0.054	0.054	0.039	0.054	0.054

Table A. 3.7: Leveraged and covenant-lite loan networks

This table reports estimation results for the panel regression in Equation (7). The dependent variable is ΔSRISK, the monthly change in SRISK, which is the systemic risk indicator proposed by Acharya et al (2017). The explanatory variables are lagged by one-month. They are: the syndication risk measures SN_RISK^{Lev} and $SN\_RISK^{Lev\&CovLite}$ which are defined in Equations (1) and (2); three proxies for network centrality, that is, degree, closeness and eigenvector centrality, which, differently from the main model are estimated on the syndicated loan networks of the leveraged and covenant-lite segments, instead of the entire syndicated loans market; the U.S. Recession dummy, based on the USRECD NBER indicator, which is equal to 1 for each month labelled as a recession by the USRECD NBER indicator and zero otherwise. The U.S. non-recession indicator is the complement of the recession dummy. Other control variables included are the lender's total assets (B$), the size of the syndicated loan market (B$), and the one-month lagged SRISK. All regressions include financial institution fixed effects. The sample period includes monthly observations from 2000 to 2022. The bottom of the table reports the number of observations, fixed effects, number of clusters (i.e., financial institutions), and adjusted R-squared values. Robust standard errors are clustered at the lender level (in parentheses).

	Degree centrality			Closeness centrality			Eigenvector centrality		
Dependent variable: ΔSRISK	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)	(9)
SN_RISK^{Lev} × U.S. Recession		0.588***			0.659***			0.592***	
		(0.106)			(0.093)			(0.113)	
SN_RISK^{Lev} × U.S. Non-Recession		-0.015			0.006			0.038	
		(0.045)			(0.045)			(0.047)	
$SN\_RISK^{Lev\&CovLite}$ × U.S. Recession			0.581***			0.651***			0.585***
			(0.102)			(0.089)			(0.108)
$SN\_RISK^{Lev\&CovLite}$ × U.S. Non-Recession			-0.034			-0.013			0.019
			(0.043)			(0.043)			(0.042)
Centrality × U.S. Recession	0.089***	0.040***	0.040***	0.060***	0.031**	0.032**	0.188***	0.078***	0.078***
	(0.020)	(0.013)	(0.013)	(0.020)	(0.012)	(0.012)	(0.041)	(0.029)	(0.029)
Centrality × U.S. Non-Recession	0.014**	0.016**	0.017**	0.025**	0.020*	0.021**	0.000	0.000	0.002
	(0.007)	(0.006)	(0.007)	(0.013)	(0.010)	(0.011)	(0.009)	(0.008)	(0.008)
Total Assets (B$)	0.002***	0.002***	0.002***	0.002***	0.002***	0.002***	0.002***	0.002***	0.002***
	(0.000)	(0.000)	(0.000)	(0.000)	(0.000)	(0.000)	(0.000)	(0.000)	(0.000)
Constant	-1.631***	-1.633***	-1.623***	-2.648***	-2.396***	-2.430***	-1.354***	-1.397***	-1.389***
	(0.352)	(0.338)	(0.336)	(0.821)	(0.686)	(0.702)	(0.280)	(0.276)	(0.276)
Control variables	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes
Observations	9,102	9,102	9,102	9,102	9,102	9,102	9,102	9,102	9,102
Financial Institution FE	95	95	95	95	95	95	95	95	95
Adj. R^2	0.049	0.056	0.056	0.043	0.055	0.055	0.048	0.055	0.055

Table A. 3.8: Additional regulatory metrics as control variables

This table reports estimation results for the panel regression in Equation (7). The dependent variable is ΔSRISK, the monthly change in SRISK, which is the systemic risk indicator proposed by Acharya et al (2017). The explanatory variables are lagged by one-month. They are: the syndication risk measures SN_RISK^{Lev} and $SN\_RISK^{Lev\&CovLite}$ which are defined in Equations (1) and (2); three proxies for network centrality, that is, degree, closeness and eigenvector centrality; the U.S. Recession dummy, based on the USRECD NBER indicator, which is equal to 1 for each month labelled as a recession by the USRECD NBER indicator and zero otherwise. The U.S. non-recession indicator is the complement of the recession dummy. In addition to the mainregression model, we add as control variables the following regulatory metrics: risk adjusted capital TIER1, risk adjusted capital TIER2, and the provisions for loan asset losses. Other control variables included are the lender's total assets (B$), the size of the syndicated loan market (B$), and the one-month lagged SRISK. All regressions include financial institution fixed effects. The sample period includes monthly observations from 2000 to 2022. The bottom of the table reports the number of observations, fixed effects, number of clusters (i.e., financial institutions), and adjusted R-squared values. Robust standard errors are clustered at the lender level (in parentheses).

			Degree centrality			Closeness centrality			Eigenvector centrality		
Dependent variable: ΔSRISK	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)	(9)	(10)	(11)
SN_RISK^{Lev} × U.S. Recession	0.610***			0.576***			0.584***			0.526***	
	(0.081)			(0.098)			(0.086)			(0.089)	
SN_RISK^{Lev} × U.S. Non-Recession	-0.035			-0.063			-0.058			-0.016	
	(0.068)			(0.069)			(0.070)			(0.068)	
$SN\_RISK^{Lev\&CovLite}$ × U.S. Recession		0.590***			0.558***			0.564***			0.506***
		(0.080)			(0.095)			(0.084)			(0.086)
$SN\_RISK^{Lev\&CovLite}$ × U.S. Non-Recession		-0.061			-0.092			-0.087			-0.044
		(0.061)			(0.062)			(0.063)			(0.061)
Centrality × U.S. Recession			0.058***	0.021**	0.021**	0.047***	0.031**	0.032**	0.149***	0.054***	0.054***
			(0.015)	(0.009)	(0.009)	(0.017)	(0.014)	(0.014)	(0.036)	(0.020)	(0.020)
Centrality × U.S. Non-recession			0.009	0.012*	0.013*	0.023**	0.025**	0.026**	-0.013	-0.014	-0.011
			(0.006)	(0.007)	(0.007)	(0.011)	(0.012)	(0.013)	(0.009)	(0.010)	(0.010)
U.S. Recession	0.352***	0.340***									
	(0.117)	(0.117)									
Total Assets (B$)	0.003***	0.003***	0.003***	0.003***	0.003***	0.003***	0.003***	0.003***	0.003***	0.003***	0.003***
	(0.000)	(0.000)	(0.001)	(0.000)	(0.000)	(0.001)	(0.000)	(0.000)	(0.001)	(0.000)	(0.000)
Risk Adjusted Capital TIER1	-0.026	-0.026	-0.017	-0.030	-0.030	-0.018	-0.025	-0.026	-0.012	-0.020	-0.020
	(0.019)	(0.019)	(0.020)	(0.021)	(0.021)	(0.019)	(0.020)	(0.020)	(0.019)	(0.018)	(0.019)
Risk Adjusted Capital TIER2	0.030	0.031	0.011	0.023	0.023	-0.011	0.010	0.010	0.013	0.027	0.028
	(0.057)	(0.058)	(0.053)	(0.055)	(0.056)	(0.049)	(0.053)	(0.053)	(0.056)	(0.056)	(0.057)
Provisions for loan asset losses	0.691***	0.696***	0.844***	0.685***	0.690***	0.895***	0.684***	0.688***	0.835***	0.688***	0.693***
	(0.120)	(0.117)	(0.108)	(0.124)	(0.121)	(0.102)	(0.123)	(0.120)	(0.099)	(0.119)	(0.115)
Constant	-1.063***	-1.031***	-1.414***	-1.240***	-1.223***	-2.353***	-2.334***	-2.370***	-1.194***	-1.068***	-1.049***
	(0.259)	(0.253)	(0.403)	(0.342)	(0.341)	(0.845)	(0.820)	(0.836)	(0.323)	(0.278)	(0.276)
Observations	9,049	9,049	9,049	9,049	9,049	9,049	9,049	9,049	9,049	9,049	9,049
Control variables	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes
Financial Institution FE	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes
Clusters	83	83	83	83	83	83	83	83	83	83	83
Adj. R^2	0.078	0.078	0.071	0.078	0.078	0.068	0.079	0.079	0.073	0.079	0.079

Table A. 3.9: Alternative SN-RISK measure based on no covenants

This table reports estimation results for the panel regression in Equation (7). The dependent variable is ΔSRISK, the monthly change in SRISK, which is the systemic risk indicator proposed by Acharya et al (2017). The explanatory variables are lagged by one-month. Differently from the main results, we include an alternative measure of syndication risk called $SN\_RISK^{\text{Covlite-no cov}}$. This measure is calculated as the ratio of the lenders' leveraged loans and cov-lite loans with no covenants, relative to the total market amount of leveraged loans and cov-lite loans with no covenants. Further, we include the following variables: three proxies for network centrality, that is, degree, closeness and eigenvector centrality; the U.S. Recession dummy, based on the USRECD NBER indicator, which is equal to 1 for each month labelled as a recession by the USRECD NBER indicator and zero otherwise. The U.S. non-recession indicator is the complement of the recession dummy. Other control variables included are the lender's total assets (B$), the size of the syndicated loan market (B$), and the one-month lagged SRISK. All regressions include financial institution fixed effects. The sample period includes monthly observations from 2000 to 2022. The bottom of the table reports the number of observations, fixed effects, number of clusters (i.e., financial institutions), and adjusted R-squared values. Robust standard errors are clustered at the lender level (in parentheses). * indicates that the estimated coefficient is significantly different from 0 at the 10% level, ** at the 5% level, and *** at the 1% level.

		Degree centrality	Closeness centrality	Eigenvector centrality
Dependent variable: ΔSRISK	(1)	(2)	(3)	(4)
$SN\_RISK^{\text{Covlite-no cov}}$ × U.S. Recession	0.691***	0.640***	0.659***	0.574***
	(0.093)	(0.102)	(0.089)	(0.105)
$SN\_RISK^{\text{Covlite-no cov}}$ × U.S. Non-recession	0.004	-0.020	-0.017	0.019
	(0.044)	(0.043)	(0.043)	(0.044)
Centrality × U.S. Recession		0.027***	0.035**	0.084***
		(0.008)	(0.014)	(0.029)
Centrality × U.S. Non-recession		0.012*	0.026*	-0.005
		(0.007)	(0.014)	(0.009)
U.S. Recession	0.486***			
	(0.130)			
Total Assets (B$)	0.002***	0.003***	0.003***	0.002***
	(0.000)	(0.000)	(0.000)	(0.000)
Constant	-1.141***	-1.373***	-2.511***	-1.160***
	(0.211)	(0.288)	(0.817)	(0.242)
Control variables	Yes	Yes	Yes	Yes
Observations	11,154	11,154	11,154	11,154
Financial Institution FE	Yes	Yes	Yes	Yes
Clusters	96	96	96	96
Adj. R^2	0.054	0.054	0.054	0.055

Table A. 3.10: Highly leveraged vs non-highly leveraged loans

This table reports estimation results for the panel regression in Equation (7). The dependent variable is ΔSRISK, the monthly change in SRISK, which is the systemic risk indicator proposed by Acharya et al (2017). The explanatory variables are lagged by one-month. Differently from the main results, we propose two alternative syndication risk measures. Panel A includes $SN\_RISK^{HighlyLev}$, which considers only highly-leveraged loans, while panel B reports $SN\_RISK^{No\text{-}HighlyLev}$, which includes leverage loans which are not higly leverage. Further, we include the following variables: the three proxies for network centrality, that is, degree, closeness and eigenvector centrality; the U.S. Recession dummy, based on the USRECD NBER indicator, which is equal to 1 for each month labelled as a recession by the USRECD NBER indicator and zero otherwise. The U.S. non-recession indicator is the complement of the recession dummy. Other control variables included are the lender's total assets (B$), the size of the syndicated loan market (B$), and the one-month lagged SRISK. All regressions include financial institution fixed effects. The sample period includes monthly observations from 2000 to 2022. The bottom of the table reports the number of observations, fixed effects, number of clusters (i.e., financial institutions), and adjusted R-squared values. Robust standard errors are clustered at the lender level (in parentheses).

Panel A. Only highly leverage loans

		Degree centrality	Closeness centrality	Eigenvector centrality
Dependent variable: ΔSRISK	(1)	(2)	(3)	(4)
$SN\_RISK^{HighlyLev}$ × U.S. Recession	0.519***	0.423***	0.489***	0.382***
	(0.099)	(0.100)	(0.097)	(0.102)
$SN\_RISK^{HighlyLev}$ × U.S. Non-Recession	0.015	0.017	0.010	0.032
	(0.043)	(0.042)	(0.043)	(0.041)
Centrality × U.S. Recession		0.036***	0.031**	0.122***
		(0.010)	(0.014)	(0.034)
Centrality × U.S. Non-recession		0.005	0.017	-0.003
		(0.006)	(0.012)	(0.009)
U.S. Recession	0.710***			
	(0.181)			
Total Assets (B$)	0.003***	0.003***	0.003***	0.003***
	(0.000)	(0.000)	(0.000)	(0.000)
Constant	-1.105***	-1.230***	-2.019***	-1.168***
	(0.216)	(0.262)	(0.728)	(0.254)
Control variables	Yes	Yes	Yes	Yes
Observations	11,154	11,154	11,154	11,154
Financial Institution FE	Yes	Yes	Yes	Yes
Clusters	94	94	94	94
Adj. R^2	0.050	0.051	0.051	0.053

Panel B. Leveraged loans which are not highly leverage

		Degree centrality	Closeness centrality	Eigenvector centrality
Dependent variable: ΔSRISK	(1)	(2)	(3)	(4)
$SN\_RISK^{No\text{-}HighlyLev}$ × U.S. Recession	0.648***	0.599***	0.623***	0.547***
	(0.107)	(0.110)	(0.106)	(0.105)
$SN\_RISK^{No\text{-}HighlyLev}$ × U.S. Non-Recession	0.038	0.028	0.027	0.055
	(0.034)	(0.036)	(0.034)	(0.037)
Centrality × U.S. Recession		0.029***	0.034**	0.085***
		(0.009)	(0.014)	(0.030)
Centrality × U.S. Non-recession		0.010	0.023*	-0.011
		(0.007)	(0.013)	(0.010)
U.S. Recession	0.574***			
	(0.159)			
Total Assets (B$)	0.002***	0.002***	0.002***	0.002***
	(0.000)	(0.000)	(0.000)	(0.000)
Constant	-1.177***	-1.374***	-2.404***	-1.148***
	(0.202)	(0.289)	(0.793)	(0.241)
Control variables	Yes	Yes	Yes	Yes
Observations	11,154	11,154	11,154	11,154
Financial Institution FE	Yes	Yes	Yes	Yes
Clusters	94	94	94	94
Adj. R^2	0.055	0.055	0.056	0.056

Table A. 3.11: Price weighted SN-RISK measure

This table reports estimation results for the panel regression in Equation (7). The dependent variable is ΔSRISK, the monthly change in SRISK, which is the systemic risk indicator proposed by Acharya et al (2017). The explanatory variables are lagged by one-month. Differently from the main results, we propose an alternative syndication risk measures, $SN\_RISK^{MktPriceW}$, which is computed by weighting each tranche amount by its corresponding Libor spread. Further, we include the following variables: the three proxies for network centrality, that is, degree, closeness and eigenvector centrality; the U.S. Recession dummy, based on the USRECD NBER indicator, which is equal to 1 for each month labelled as a recession by the USRECD NBER indicator and zero otherwise. The U.S. non-recession indicator is the complement of the recession dummy. Other control variables included are the lender's total assets (B$), the size of the syndicated loan market (B$), and the one-month lagged SRISK. All regressions include financial institution fixed effects. The sample period includes monthly observations from 2000 to 2022. The bottom of the table reports the number of observations, fixed effects, number of clusters (i.e., financial institutions), and adjusted R-squared values. Robust standard errors are clustered at the lender level (in parentheses).

		Degree centrality	Closeness centrality	Eigenvector centrality
Dependent variable: ΔSRISK	(1)	(2)	(3)	(4)
$SN\_RISK^{SpreadWeight}$ × U.S. Recession	0.749***	0.720***	0.726***	0.629***
	(0.113)	(0.133)	(0.114)	(0.125)
$SN\_RISK^{SpreadWeight}$ × U.S. Non-Recession	0.024	0.013	0.013	0.030
	(0.038)	(0.038)	(0.038)	(0.039)
Centrality × U.S. Recession		0.023**	0.034**	0.078**
		(0.011)	(0.017)	(0.031)
Centrality × U.S. Non-recession		0.010	0.026*	-0.004
		(0.007)	(0.016)	(0.010)
U.S. Recession	0.457***			
	(0.156)			
Total Assets (B$)	0.002***	0.002***	0.003***	0.002***
	(0.000)	(0.000)	(0.000)	(0.000)
Constant	-1.176***	-1.395***	-2.600***	-1.189***
	(0.217)	(0.303)	(0.932)	(0.264)
Observations	10,104	10,104	10,104	10,104
Control variables	Yes	Yes	Yes	Yes
Financial Institution FE	Yes	Yes	Yes	Yes
Clusters	95	95	95	95
Adj. R^2	0.055	0.055	0.056	0.056

Table A. 3.12: Alternative systemic risk measure: ΔLRMES

This table reports estimation results for the panel regression in Equation (7). The dependent variable is ΔLRMES, the monthly change in LRMES, which is the systemic risk indicator proposed by Brownlees and Engle (2017). The explanatory variables are lagged by one-month. They are: the syndication risk measures SN_RISK^{Lev} and $SN\_RISK^{Lev\&CovLite}$ which are defined in Equations (1) and (2); three proxies for network centrality, that is, degree, closeness and eigenvector centrality; the U.S. Recession dummy, based on the USRECD NBER indicator, which is equal to 1 for each month labelled as a recession by the USRECD NBER indicator and zero otherwise. The U.S. non-recession indicator is the complement of the recession dummy. Other control variables included are the lender's total assets (B$), the size of the syndicated loan market (B$), and the one-month lagged SRISK. All regressions include financial institution fixed effects. The sample period includes monthly observations from 2000 to 2022. The bottom of the table reports the number of observations, fixed effects, number of clusters (i.e., financial institutions), and adjusted R-squared values. Robust standard errors are clustered at the lender level (in parentheses).

			Degree centrality			Closeness centrality			Eigenvector centrality		
Dependent variable: ΔLRMES	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)	(9)	(10)	(11)
SN_RISK^{Lev} × U.S. Recession	0.330***			0.232***			0.290***			0.218***	
	(0.071)			(0.076)			(0.069)			(0.072)	
SN_RISK^{Lev} × U.S. Non-Recession	0.052			0.047			0.064			0.052	
	(0.049)			(0.046)			(0.047)			(0.047)	
$SN\_RISK^{Lev\&CovLite}$ × U.S. Recession		0.327***			0.229***			0.287***			0.215***
		(0.072)			(0.077)			(0.070)			(0.073)
$SN\_RISK^{Lev\&CovLite}$ × U.S. Non-Recession		0.047			0.041			0.058			0.046
		(0.049)			(0.045)			(0.047)			(0.047)
Centrality × U.S. Recession			0.062***	0.047***	0.047***	0.033*	0.020	0.020	0.189***	0.150***	0.150***
			(0.013)	(0.014)	(0.014)	(0.018)	(0.017)	(0.017)	(0.040)	(0.043)	(0.043)
Centrality × U.S. Non-recession			0.003	0.001	0.001	-0.003	-0.009	-0.009	0.009	0.004	0.004
			(0.010)	(0.009)	(0.009)	(0.016)	(0.016)	(0.016)	(0.032)	(0.031)	(0.031)
U.S. Recession	1.545***	1.541***									
	(0.230)	(0.230)									
Total Assets (B$)	0.002**	0.002**	0.002**	0.002**	0.002**	0.002**	0.001**	0.001**	0.002**	0.001**	0.001**
	(0.001)	(0.001)	(0.001)	(0.001)	(0.001)	(0.001)	(0.001)	(0.001)	(0.001)	(0.001)	(0.001)
Constant	12.418***	12.423***	12.418***	12.470***	12.470***	12.566***	12.901***	12.887***	12.453***	12.487***	12.488***
	(0.546)	(0.546)	(0.613)	(0.609)	(0.609)	(1.074)	(1.030)	(1.031)	(0.594)	(0.593)	(0.593)
Control variables	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes
Observations	11,154	11,154	11,154	11,154	11,154	11,154	11,154	11,154	11,154	11,154	11,154
Financial Institution FE	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes
Clusters	96	96	96	96	96	96	96	96	96	96	96
Adj. R^2	0.178	0.178	0.175	0.176	0.176	0.176	0.178	0.178	0.176	0.177	0.177

Table A. 3.13: Syndication risk and network centrality as determinants of systemic risk - alternative model specification

This table reports estimation results for the panel regression in Equation (7). The dependent variable is ΔSRISK, the monthly change in SRISK, which is the systemic risk indicator proposed by Acharya et al (2017). The explanatory variables are lagged by one-month. Differently from the main analysis, we introduce as standalone terms and interacted with the U.S. Recession variable the syndication risk measures SN_RISK^{Lev} and $SN\_RISK^{Lev\&CovLite}$ which are defined in Equations (1) and (2). We also include three proxies for network centrality, that is, degree, closeness and eigenvector centrality; and the U.S. Recession dummy, based on the USRECD NBER indicator, which is equal to 1 for each month labelled as a recession by the USRECD NBER indicator and zero otherwise. The U.S. non-recession indicator is the complement of the recession dummy. Other control variables included are the lender's total assets (B$), the size of the syndicated loan market (B$), and the one-month lagged SRISK. All regressions include financial institution fixed effects. The sample period includes monthly observations from 2000 to 2022. The bottom of the table reports the number of observations, fixed effects, number of clusters (i.e., financial institutions), and adjusted R-squared values. Robust standard errors are clustered at the lender level (in parentheses). * indicates that the estimated coefficient is significantly different from 0 at the 10% level, ** at the 5% level, and *** at the 1% level.

			Degree centrality			Closeness centrality			Eigenvector centrality		
Dependent variable: ΔSRISK	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)	(9)	(10)	(11)
SN_RISK^{Lev}	2.086			-0.089			0.113			3.784	
	(4.704)			(4.511)			(4.528)			(4.783)	
SN_RISK^{Lev} × U.S. Recession	0.678***			0.647***			0.667***			0.544***	
	(0.075)			(0.092)			(0.078)			(0.086)	
$SN\_RISK^{Lev\&CovLite}$		0.453			-1.874			-1.599			2.043
		(4.384)			(4.373)			(4.338)			(4.449)
$SN\_RISK^{Lev\&CovLite}$ × U.S. Recession		0.687***			0.659***			0.676***			0.554***
		(0.075)			(0.093)			(0.078)			(0.086)
Centrality			0.011	0.011	0.012*	0.029*	0.025*	0.026*	-0.001	-0.007	-0.005
			(0.007)	(0.007)	(0.007)	(0.015)	(0.013)	(0.014)	(0.008)	(0.009)	(0.009)
Centrality × U.S. Recession			0.061***	0.016**	0.015**	0.030***	0.009***	0.009***	0.197***	0.091***	0.089***
			(0.013)	(0.006)	(0.007)	(0.007)	(0.003)	(0.003)	(0.044)	(0.026)	(0.026)
U.S. Recession	0.498***	0.486***									
	(0.131)	(0.130)									
Total Assets (B$)	0.002***	0.002***	0.002***	0.003***	0.003***	0.002***	0.003***	0.003***	0.002***	0.002***	0.002***
	(0.000)	(0.000)	(0.000)	(0.000)	(0.000)	(0.000)	(0.000)	(0.000)	(0.000)	(0.000)	(0.000)
Constant	-1.160***	-1.142***	-1.391***	-1.379***	-1.374***	-2.693***	-2.481***	-2.509***	-1.182***	-1.167***	-1.160***
	(0.216)	(0.211)	(0.315)	(0.289)	(0.288)	(0.905)	(0.800)	(0.816)	(0.262)	(0.243)	(0.242)
Control Variables	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes
Observations	11,154	11,154	11,154	11,154	11,154	11,154	11,154	11,154	11,154	11,154	11,154
Financial Institution FE	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes
Clusters	96	96	96	96	96	96	96	96	96	96	96
Adj. R^2	0.054	0.054	0.045	0.054	0.054	0.042	0.054	0.054	0.048	0.055	0.055

Table A. 3.14: Analysis of different periods of recession

This table reports estimation results for the panel regression in Equation (7). The dependent variable is ΔSRISK, the monthly change in SRISK, which is the systemic risk indicator proposed by Acharya et al (2017). The explanatory variables are lagged by one-month. Differently from the main analysis, we distinguish three different periods of recession in this specification. Recession period 1 spans from April 2001 to November 2001, Recession period 2 spans from January 2008 to June 2009, and Recession period 3 includes March and April 2020. We introduce as stand-alone terms and interacted with the three U.S. Recessions variables separatly the syndication risk measures SN_RISK^{Lev} and $SN_RISK^{Lev\&CovLite}$which are defined in Equations (1) and (2), and the three proxies for network centrality, that is, degree, closeness and eigenvector centrality. The U.S. non-recession indicator is the complement of the recession dummy. Other control variables included are the lender's total assets (B$), the size of the syndicated loan market (B$), and the one-month lagged SRISK. All regressions include financial institution fixed effects. The sample period includes monthly observations from 2000 to 2022. The bottom of the table reports the number of observations, fixed effects, number of clusters (i.e., financial institutions), and adjusted R-squared values. Robust standard errors are clustered at the lender level (in parentheses). * indicates that the estimated coefficient is significantly different from 0 at the 10% level, ** at the 5% level, and *** at the 1% level.

			Degree centrality			Closeness centrality			Eigenvector centrality		
Dependent variable: ΔSRISK	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)	(9)	(10)	(11)
SN_RISK^{Lev}	0.025			0.012			0.004			0.042	
	(0.042)			(0.042)			(0.040)			(0.044)	
SN_RISK^{Lev} × Recession period 1	0.100			0.093			0.095			0.048	
	(0.102)			(0.148)			(0.115)			(0.135)	
SN_RISK^{Lev} × Recession period 2	0.612***			0.527***			0.591***			0.516***	
	(0.127)			(0.161)			(0.133)			(0.156)	
SN_RISK^{Lev} × Recession period 3	2.507***			1.825**			2.388***			1.949**	
	(0.773)			(0.829)			(0.783)			(0.832)	
$SN\_RISK^{Lev\&CovLite}$		0.012			-0.004			-0.010			0.027
		(0.040)			(0.041)			(0.039)			(0.042)
$SN\_RISK^{Lev\&CovLite}$ × Recession period 1		0.105			0.102			0.100			0.055
		(0.101)			(0.147)			(0.114)			(0.134)
$SN\_RISK^{Lev\&CovLite}$ × Recession period 2		0.617***			0.535***			0.597***			0.524***
		(0.128)			(0.164)			(0.135)			(0.157)
$SN\_RISK^{Lev\&CovLite}$ × Recession period 3		2.710***			2.064**			2.598***			2.196***
		(0.731)			(0.815)			(0.745)			(0.811)
Centrality			0.014*	0.013*	0.014*	0.033**	0.030**	0.030**	-0.004	-0.009	-0.008
			(0.007)	(0.007)	(0.008)	(0.015)	(0.014)	(0.015)	(0.007)	(0.008)	(0.008)
Centrality × Recession period 1			0.009***	0.003	0.002	0.005***	0.002	0.002	0.041***	0.029	0.028
			(0.003)	(0.008)	(0.008)	(0.002)	(0.004)	(0.004)	(0.011)	(0.027)	(0.027)
Centrality × Recession period 2			0.065***	0.025**	0.024**	0.030***	0.011***	0.011***	0.176***	0.074**	0.073**
			(0.014)	(0.011)	(0.011)	(0.008)	(0.004)	(0.004)	(0.041)	(0.029)	(0.029)
Centrality × Recession period 3			0.328***	0.167***	0.149***	0.118***	0.043***	0.038***	0.717***	0.330***	0.287***
			(0.078)	(0.053)	(0.050)	(0.032)	(0.016)	(0.014)	(0.174)	(0.114)	(0.104)
Recession period 1	0.125	0.115									
	(0.182)	(0.181)									
Recession period 2	0.509***	0.500***									
	(0.179)	(0.180)									
Recession period 3	1.648**	1.446**									
	(0.637)	(0.560)									
Total Assets (B$)	0.002***	0.002***	0.002***	0.002***	0.002***	0.002***	0.002***	0.002***	0.002***	0.002***	0.002***
	(0.000)	(0.000)	(0.000)	(0.000)	(0.000)	(0.000)	(0.000)	(0.000)	(0.000)	(0.000)	(0.000)
Constant	-0.949***	-0.930***	-1.272***	-1.244***	-1.237***	-2.784***	-2.539***	-2.550***	-0.939***	-0.905***	-0.897***
	(0.198)	(0.194)	(0.309)	(0.287)	(0.286)	(0.932)	(0.842)	(0.853)	(0.231)	(0.218)	(0.216)
Control Variables	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes
Observations	11,154	11,154	11,154	11,154	11,154	11,154	11,154	11,154	11,154	11,154	11,154
Financial Institution FE	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes
Clusters	96	96	96	96	96	96	96	96	96	96	96
Adj. R^2	0.073	0.074	0.066	0.076	0.077	0.052	0.074	0.076	0.063	0.075	0.076

4. How Climate Risk Shapes U.S. Systemic Stability through Syndicated Lending

4.1. Introduction

Building on the report *Climate-related risk drivers and their transmission channels* (Bank for International Settlements, 2021), which highlights that "there are multiple climate-related risk drivers that are increasingly likely to translate into significant financial risks for banks" and emphasizes the need to understand how these drivers affect bank exposures and income, this study aims to contribute to this discussion by leveraging currently available data to examine banks' exposure to a range of climate risk drivers. In line with the framework proposed by regulators, our analysis considers both acute and chronic physical factors, as well as key transition factors such as policy developments and market sentiment.[14] In this context, strengthening the financial system's resilience to climate-related risks has become a priority for regulatory authorities, prompting various initiatives. Notably, the Task Force on Climate-related Financial Disclosures (TCFD) was established in 2015, the Network for Greening the Financial System (NGFS) in 2017, the Net-Zero Banking Alliance (NZBA) launched in 2021, and the Sustainable Finance Disclosure Regulation (SFDR) was implemented in the EU the same year. These initiatives share the goal of enhancing the financial system's resilience to climate-related risks by promoting transparency, standardizing climate risk disclosures, and encouraging sustainable investment and lending practices. We can distinguish climate risks into two main categories: transition risks and physical risks (Monasterolo, 2020). Transition risks result from the shift toward a more sustainable economy, which can reduce asset values, lower investment returns, and raise operational costs in sectors such as coal, oil, and gas. Physical risks arise from the direct impacts of climate change, including higher temperatures and extreme weather events, which can increase market volatility, weaken credit quality, and elevate default rates.

Drawing on Bolton et al. (2020), who highlight the connection between climate risk and systemic financial vulnerability, we examine how banks incorporate climate risks into their lending decisions. This approach sheds light on the channels that can amplify or mitigate systemic vulnerabilities and provides insights for policymakers and stakeholders seeking to

[14] See for reference Figure 1 – *Financial risks from climate risk drivers* in *Climate-related risk drivers and their transmission channels* (BCBS, 2021).

enhance the resilience of the financial system in the face of climate-related challenges. While syndicated lending literature has expanded rapidly in the post-global financial crisis period, reflecting its role as a key funding source for non-financial corporations (Sufi, 2007), its potential to advance environmental objectives remains largely underexplored (Saharti et al., 2024). This study aims to address part of this gap by proposing a holistic approach that combines several climate-related indicators, both from the literature and newly developed, and uses banks' syndicated lending to explore how climate risk affects systemic stability. Our framework analyzes banks' portfolios following the methodology of Blickle et al. (2020). It links these portfolios to borrowers' environmental performance. This performance captures not only emissions but also alignment with climate goals, innovation in green technologies, resource efficiency, and disclosure practices. As emissions are slow to adjust, environmental scores offer timely insights into firms' directional commitment to sustainability. This distinction is critical: as Cohen et al. (2020) argue, firms with high emissions may simultaneously lead in green innovation, making them central to a low-carbon transition and challenging simplistic "green vs. brown" classifications.

This market enables us to examine both the structure and regional exposure of lender portfolios, by disaggregating lead and participant banks. Our analysis concentrates on the U.S. for two reasons: first, the share allocation methodology of Blickle et al. (2020) is based on the U.S. syndicated loan market; second, Yang et al. (2023) identify the U.S. as a core node in transmitting transition risk globally. We contribute to the literature on syndicated loans by introducing a novel perspective centred on bank behaviour, employing a comprehensive set of indicators designed to examine multiple relevant dimensions of climate-related risk. First, to our knowledge, this is the first study to apply the methodology developed by Blickle et al. (2020) to construct climate risk measures grounded in syndicated loan data. This approach offers a robust measure of banks' syndicated portfolios, providing the basis for constructing our climate-related variables used to examine how climate risks affect systemic risk in the banking sector. We introduce a market-level indicator that captures each bank's commitment to green lending. Second, we assess the impact of short- and long-term physical climate risks by analysing climate anomalies across U.S. regions, adjusted for banks' lending exposures in those areas. Third, we explore how shifts in banks' systemic risk relate to climate risk variables from existing literature, particularly those based on textual analysis, an increasingly valuable tool for capturing market perceptions of climate threats. Our findings indicate that lending to environmentally focused firms strengthens a bank's resilience. This suggests that such banks may be perceived as less exposed to climate risks due to their engagement with more sustainable borrowers. However, systemic risk in the banking sector is amplified not only by extreme events but also by short-term climate anomalies, which often act as precursors to more severe shocks. In addition, heightened attention to climate policy appears to increase systemic risk cross-variation, likely reflecting the introduction of additional uncertainty in the regulatory and market environment.

Regarding physical climate risks, we find that short-term precipitation anomalies in the Eastern U.S., though temporary, significantly contribute to systemic instability, possibly because they serve as early indicators of more severe events, such as tropical cyclones, to which the region is particularly vulnerable. In the Southern region, extreme event-related costs are strongly linked to higher systemic risk, reflecting the concentration of syndicated lending in Texas, a major market hub. Texas also plays a crucial role in the energy transition, as its oil and gas firms significantly influence the U.S. economy, amplifying the impact of regional climate shocks. Our findings support those of Conlon et al. (2024) and Curcio et al. (2023), demonstrating a strong correlation between the economic effects of climate-related extreme events and the systemic risk measures of U.S. banks.[15] However, our regional analysis reveals that the impact of climate events on systemic risk varies across U.S. regions depending on local banking concentrations. If a major climate shock occurs in a region where a bank has no exposure, it assumes a zero value for the purpose of explaining bank's systemic risk. Conversely, in regions where a bank has a significant presence, the effects of climate anomalies are amplified. For example, increasing climate change physical events in the Eastern and Southern regions heighten systemic

[15] Looking at the European financial system, Jourde and Moreau (2022) examine both transition and physical risks faced by European banks in relation to climate change. Unlike Jourde and Moreau (2022), who find no significant relationship between physical climate risks and systemic risk in Europe, our analysis of the U.S. financial system provides empirical evidence suggesting that higher levels of lending activity in regions characterised by greater exposure to climate anomalies lead to an increase in bank systemic risk attributable to physical climate risk.

risk for banks due to their substantial loan exposure there. Building on Curcio et al. (2023), we incorporate short-term climate anomalies, environmental-lending choices, and literature-based measures into our analysis. Rather than focusing solely on extreme events, we seek to account for a broader set of climate-related factors, as banks' systemic risk may be influenced by various dimensions of climate conditions. In line with this perspective, our findings on physical climate factors suggest that short-term precipitation anomalies in the Eastern region may be positively and significantly associated with cross-bank variations in systemic risk.

Lastly, we find that the climate policy factor developed by Faccini et al. (2023) is associated with rising systemic risk in the short-term, possibly reflecting the financial system's heightened sensitivity during transitional periods marked by regulatory shifts and policy uncertainty.[16] Our results on the impact of climate media attention on systemic risk differ from Liu et al. (2024), who find that climate policy uncertainty is associated with lower bank systemic risk, particularly in countries with high innovation capacity and climate readiness. Liu et al. (2024) employ a different methodology that analyses indices distinct from those used by Faccini et al. (2023) and focused specifically on G20 countries. Differently, our approach includes additional climate-related variables and portfolio measures, which may capture marginal effects on systemic risk that cannot be identified through policy announcements alone. This approach allows us to explore the marginal impact of climate policy within a model that considers several climate factors. The factor introduced in Faccini et al. (2023) is constructed using textual analysis of Reuters news and captures media attention to U.S. climate-related policy debate and legislation. It provides a proxy for transition risk which can be used to assess its impact on firms' valuations. Faccini et al. (2023) find that this factor is priced in U.S. stock returns, unlike physical climate risks. They explain this result using the framework of intertemporal hedging. In other words, investors change their portfolios based on which future climate policies they expect to enter into force. And, when this indicator is lower, indicating less news about climate policy, investors consider this as a sign that climate regulation might increase soon, so they become more cautious. Our findings indicate a positive association between climate policy and

[16] Jung et al. (2025) estimate that, by the end of 2020, marginal climate risk exposure for the four largest U.S. banks ranged between $45 and $90 billion each. Combined, this amounts to roughly $260 billion, equivalent to about 28% of their total equity. Such figures highlight the substantial potential impact that transition-related policies could exert on the banking sector.

banks’ systemic risk, likely reflecting the uncertainty that policy implementation and shifting political attitudes introduce into the financial system.

In this context, findings from Mueller and Sfrappini (2022) suggest that banks can strategically reduce credit exposure to companies facing climate-related regulatory risks. Instead of supporting high-risk firms, banks might prefer lending to those less affected by regulations or those that could benefit from them. This strategic approach is essential, as the impact of climate risk on financial institutions can be further understood through loan default analysis, as discussed by Battiston et al. (2021). Recently, Jung et al. (2025) introduce a measure called Climate Risk Expected Capital Shortfall (CRISK), which effectively captures the relationship between banks’ lending practices, climate risk, and financial risks tied to climate-sensitive loans. Their findings indicate that a higher climate beta correlates with greater exposure to brown industries, increasing the risk of defaults on related loans.

Building on the research of Aevoae et al. (2023), which indicates that banks' ESG scores can reduce financial distress, we explore in our robustness section how banks' lending choices, based on borrowers' Environmental-friendly Scores, impact their exposure to climate-related systemic risk. By analysing banks’ lending portfolios, we aim to present a more objective measure focused on borrowers, rather than relying on the lenders’ self-reported ESG scores, which could be potentially biased. Our findings confirm Aevoae et al. (2023) results and indicate that banks’ lending more to environmentally-friendly borrowers tend to lower their systemic risk, likely because these borrowers often adopt sustainable practices that make them more resilient to climate shocks and new policies. Additionally, lending to environmentally conscious borrowers allows banks to align with the growing regulatory focus on sustainability. This alignment can help reduce reputational risks associated with financing environmentally harmful activities and promote long-term financial stability.

While previous studies have primarily used broad market-based indicators to examine the link between climate and systemic risk (Kanas et al., 2023; Curcio et al., 2023; Conlon et al., 2024), our approach complements this literature by constructing indicators based on banks’ lending portfolio decisions. These indicators provide a closer reflection of each bank’s approach to addressing climate change, while market-level indicators often reflect broader government policies and regulatory influences. Adopting this bank-level perspective enables us to explore how individual lending practices relate to systemic risk and to consider the environmental risks present within specific loan portfolios. We extend this approach to physical climate risk variables, taking into account banks' regional exposures to provide a more nuanced estimate of the relationship between climate risk and systemic vulnerability. To support this analysis, we include physical climate data, including temperature and precipitation from the National Centers for Environmental Information (NCEI), allowing for a careful assessment of environmental impacts. To complement our analysis, we incorporate several climate risk indicators from the existing literature, which rely primarily on textual analysis to capture how markets perceive climate-related threats. Specifically, we use indices developed by Engle et al. (2020), Ardia et al. (2023), Sautner et al. (2023), and Faccini et al. (2023). These indicators enrich our study by providing a comprehensive view of media attention around climate risks, which, as the primary source of funding and credit allocation, plays a critical role in shaping banks' risk exposure. Our findings show that mainly climate policy (Faccini et al., 2023) influences systemic stability.

Several studies examine climate risks within the context of the syndicated loan market, focusing primarily on loan pricing, widely considered the key metric for capturing information about how lenders perceive and price climate-related risks. For example, from the perspective of physical climate risks, Javadi and Masum (2021) explore how climate change impacts firms' borrowing costs, using the Palmer Drought Severity Index (PDSI) as a proxy. Their results show that companies located in areas more vulnerable to climate change encounter significantly higher interest rates on bank loans. This underscores the growing awareness among lenders in the syndicated market of the necessity to integrate climate change as an important risk factor in loan pricing. By looking at borrowers' emissions, Ehlers et al. (2022) examine the relationship between climate risk and borrowing costs. They find that firms with higher carbon intensities face a risk premium since the Paris Agreement, although this premium is not restricted to specific industries. Its magnitude, however, appears relatively small compared to the actual risks involved. Ehlers et al. (2022) also investigate the role of "green" banks[17], discovering that these institutions tend to lend less to high carbon emitters but do not charge a higher carbon premium compared to other banks. Similarly, Reghezza et al. (2022) analyze loan-level data related to firms' greenhouse gas emissions and observe a significant shift linked to the Paris Agreement. They report that since the 2015 Paris Agreement, European banks have allocated approximately

[17] Ehlers et al. (2022) define a bank as green if it has signed either the Equator Principles or the United Nations Environment Programme Finance Initiative (UNEP FI)

3 percentage points less of their lending to high-polluting firms compared to those classified as "green". In the post-Paris Agreement context, Degryse et al. (2023) highlight that green banks have begun to offer more favourable loans in the international syndicated market to firms that prioritize environmental sustainability. In the context of emerging markets, Ho and Wong (2023) find that climate risks have started to influence loan pricing for high-emission sectors since the Paris Agreement. Their results suggest that "green" banks[18] are likely to impose higher loan spreads for emissions-intensive firms after the agreement, along with stricter contractual conditions, such as shorter repayment periods and increased collateral, particularly for firms with higher default risk. Additionally, the study highlights that banks may enforce tighter contractual terms for firms with significant emissions, especially when those firms are associated with elevated default risks.

The rest of the paper is structured as follows. Section 4.2 outlines the methodology used in this study, and Section 4.3 presents the data utilized for our analysis. Section 4.4 presents the primary empirical findings along with robustness tests, and Section 4.5 concludes the paper.

4.2. Methodology

In this section, we describe the variables used to proxy banks' exposure to climate risks and the econometric model applied in our empirical analysis. To measure how much of the syndicated market each lender holds in its portfolio, we use the approach of Blickle et al. (2020), which estimates each lender's share after adjusting for the portion quickly sold after origination. We then aggregate the amount of syndicated loans held by each lender on a monthly basis.

4.2.1. Climate risk measures

We aim to understand how climate risk relates to systemic risk by examining various factors. Our first focus is on banks' portfolios of environmentally responsible borrowers. To this end, we examine borrowers' environmental scores, which capture their sustainability practices. Next, we look at the physical climate risks that arise from the activities of lenders in the

[18] Ho and Wong (2023) consider a bank as green when it meets two criteria: firstly, it is a member of UNEP FI, and secondly, either the bank itself or its ultimate parent holding firm has voluntarily disclosed CO_2 emission information of the organization.

syndicated loan market. For this analysis, we obtain relevant data from the National Centers for Environmental Information (NCEI). To complement the analysis with measures reflecting market attention to climate issues, we also include climate risk indices from recent studies by Engle et al. (2020), Ardia et al. (2023), Sautner et al. (2023), and Faccini et al. (2023). This multifaceted approach allows us to better understand the interplay between climate risk and systemic risk in banking. Table 4.1 summarizes the climate risk variables used to evaluate environmental impacts and lender exposure, providing a brief description along with the source of each variable.

Table 4.1: Climate risk variable description

This table provides a comprehensive overview of various climate risk variables utilized in assessing environmental impacts and lender exposure.

Variable name	**Source**	**Description**
Environmentally_friendly_index	Thomson reuters Eikon and self-calculation	The *Environmentally_friendly_index* assesses the market share of each lender's environmentally-focused portfolio within the syndicated loans market. The numerator consists of the total monthly loans from each lender, adjusted for the borrowers' scores, while the denominator represents the overall total at the market level.
Lender environmental score	Thomson reuters Eikon	Lender's environmental score.
Temperature regional−weighted index	National Centers for Environmental Information and self-calculation	The *Temperature regional-weighted index* evaluates the temperature anomalies recorded in each of the four regions (western, eastern, central, and southern). Each regional index is weighted according to the lender's market share, which reflects the volume of loans issued in each region relative to the total U.S. market. The temperature anomaly is calculated by subtracting the average temperature recorded from 1901 to 2000.
Precipitation regional−weighted index	National Centers for Environmental Information and self-calculation	The P*recipitation regional-weighted index* assesses the precipitation anomalies documented in each of the four regions (western, eastern, central, and southern). Each regional-based index is weighted according to the lender's market share, which is based on the volume of loans issued in each region relative to the total U.S. market. The precipitation anomaly is calculated by taking the difference from the average precipitation level recorded between 1901 and 2000.
Palmer drought severity regional−weighted index	National Centers for Environmental Information and self-calculation	The Palmer drought severity regional−weighted index assesses the PDSI value documented in each of the four regions (western, eastern, central, and southern). Each regional-based index is weighted according to the lender's market share, which is based on the volume of loans issued in each region relative to the total U.S. market.
Extreme regional−weighted impact cost	National Centers for Environmental Information and self-calculation	The *Extreme regional-weighted index* assesses the cost of billion-dollar extreme events damages, documented in each of the four regions (western, eastern, central, and southern). Each regional-based index is weighted according to the lender's market share, which is based on the volume of loans issued in each region relative to the total U.S. market.

(Table 4.1 - continues in the next page)

(Table 4.1 - continued)

CCExposure_lender_index	Sautner et al. (2023): https://osf.io/fd6jq/files/osfstorage and self-calculation	The *CCExposure_lender_index* primarily utilizes the *CCExposure index* developed by Sautner et al. (2023), which quantifies the relative frequency of bigrams related to climate change found in earnings conference call transcripts. In the numerator, the *CCExposure_lender_index* aggregates loans at the lender level, weighted by the CCExposure of the borrowers, while the denominator totals the CCExposure amounts at the market level.
Wall Street Journal climate change news index	Engle et al. (2020): https://drive.google.com/file/d/1pCHmcebmOwrVCFim78ALhB51c3h1qt2T/view	The *Wall Street Journal (WSJ) climate change news index* is based on the research conducted by Engle et al. (2020). It quantifies the coverage of climate change in the WSJ by comparing its content to a defined vocabulary of climate-related terms.
Crimson Hexagon (CH) Negative climate change news index	Engle et al. (2020): https://drive.google.com/file/d/1pCHmcebmOwrVCFim78ALhB51c3h1qt2T/view	The *Crimson Hexagon (CH) Negative climate change news index* is based on the research conducted by Engle et al. (2020). This index is designed to focus specifically on negative climate news.
Media Climate Change Concerns index (MCCC)	Ardia et al. (2023): https://www.dropbox.com/s/jwjh4b08zvq09nv/LICENSE.txt?dl=0	The *Media Climate Change Concerns index (MCCC)* is derived from the research by Ardia et al. (2023). It reflects changes in public concerns about climate change by analyzing news articles through risk and sentiment lexicons to evaluate discussions on future risks and perceptions of escalating risk.
Climate change risk factors: natural disasters, global warming, international summits, and U.S. climate policy.	Faccini et al. (2023): https://docs.google.com/spreadsheets/d/1JW7l_ZLCsPm7wPOrSaEZzMedZJ7M2opK/edit?gid=1333933877#gid=1333933877	The four climate change risk factors - natural disasters, global warming, international summits, and U.S. climate policy - are derived from the research by Faccini et al. (2023).

4.2.1.1. Environmentally-Friendly Index for Bank Borrower Lending

The first metric we introduce is the bank's $Environmentally\_friendly\_index$. This index assesses lenders' exposure to environmental risk by analysing their loan portfolios in relation to the environmental performance of their borrowers. The numerator captures the total monthly loan amount issued by each lender, weighted by the environmental scores of the respective borrowers. The denominator reflects the corresponding total loan amount at the overall market level. This measure, however, has some limitations. First, it only includes borrowers for whom environmental data are available, which may reduce the sample size and representativeness. Second, large loan volumes from a few borrowers can heavily influence the numerator, potentially skewing the measure toward the lending behaviour of those particular cases. Despite these limitations, the index offers a useful proxy for assessing a lender's commitment to supporting a greener economy through lending to borrowers with stronger environmental credentials. We define the $Environmentally\_Friendly\_Index$ for each bank i, month t, as follows:

$$Environmentally\_friendly\_index_{i,t} = \frac{\sum_{i,j,k,t} Loan\ environemtally{-}weighte\quad amount_{i,j,k,t}}{\sum_{j,k,t} Loan\ environemtally{-}weighted\ amount_{j,k,t}} \tag{10}$$

In this formula, i denotes each lender in the syndicated loans market. The numerator aggregates the total loan issuance from lenders, weighted by each borrower's environmental score at the level of lender i for each month t. The denominator sums the environmentally-weighted loan amounts at the monthly level, reflecting the total amount of environmentally-weighted loans in the market. By design, these measures range from 0 to 1.

Using a methodology similar to that applied in constructing the $Environmentally\_friendly\_index_{i,t}$, we assess lenders' exposure to firms' climate change transition risk by introducing a metric based on the $CCExposure\ score$ developed by Sautner et al. (2023). To build this measure, we combine manual matching with automated procedures using the dataset provided by Sautner et al. (2023). Specifically, the $CCExposure\_lender\_index_{i,t}$ is calculated by replacing the borrowers' environmental scores with their $CCExposure\ score$. The $CCExposure\ score$ captures firms' transition risk by quantifying the relative frequency of climate change–related bigrams in firms' earnings conference call transcripts, computed as the number of relevant bigrams divided by the total number of bigrams in each transcript.

4.2.1.2. Proxy of climate physical risks

To assess the impact of climate-related physical risks on systemic risk stemming from banks' lending activities in the syndicated loans market, we introduce several measures. Each measure is calculated by weighting the loans issued by a bank in a specific region relative to the bank's total loans issued nationwide. This approach ensures that regions with larger loan volumes have a greater impact on the overall climate risk assessment. Our main hypothesis is that increased lending in areas that are most vulnerable to climate change will heighten systemic risk for lenders, due to the increased exposure to environmental disruptions that could adversely affect borrower performance. For example, if a significant climate anomaly occurs in the Central region during a specific month, but the bank has no lending exposures in that region, the indicator will be zero. Conversely, temperature anomalies in regions where the bank has significant exposure are more meaningful, and the indicator value reflects both the climate anomaly and the bank's lending exposure in those regions.

Our first climate risk variables focus on temperature and precipitation anomalies across the four regions identified by the U.S. National Weather Service: Western, Southern, Central, and Eastern. Our primary goal is to determine whether an increase in lending activity in these climate-sensitive regions is associated with heightened systemic risk for lenders. For each lender i and month t, we calculate the $Temperature\ regional - weighted\ index$ as follows:

$$Temperature\ regional - weighted\ index_{i,k,t} =$$

$$= Regional\ temperature\ anomaly_{k,t} \times \frac{Lender\ regional\ amount_{i,k,t}}{Lender\ market\ amount_{i,t}}, \tag{11}$$

where the $Regional\ temperature\ anomaly_{k,t}$ represents the temperature anomaly recorded in each of the four regions k for month t. The $Lender\ regional\ amount_{i,k,t}$ indicates the total value of syndicated loans provided by lender i in month t within one of the four regions k considered (Eastern, Western, Southern, or Central). The $Lender\ market\ amount_{i,t}$ represents the overall amount of syndicated loans issued by the lender in the U.S. market for that month. Using a similar method, we construct the $Precipitation\ regional - weighted\ index_{i,k,t}$ for lender i, which captures the precipitation anomaly in region k in month t , weighted by the lender's share of syndicated loan issuance in that region.

To incorporate a comprehensive index that takes into consideration both temperature and precipitation as key factors in estimating drought conditions across U.S. regions, we include the Palmer Drought Severity Index (PDSI) as an alternative indicator of climate change. While temperature and precipitation anomalies indicate short-term climate conditions, the PDSI quantifies the severity and duration of droughts by incorporating long-term data on precipitation and temperature, providing a composite measure of drought severity. We define the regionally-weighted PDSI index as:

$$PDSI\ regional - weighted\ index_{i,k,t} =$$

$$= Regional\ PDSI_{k,t} \times \frac{Lender\ regional\ amount_{i,k,t}}{Lender\ market\ amount_{i,t}}, \tag{12}$$

Using a similar approach, we introduce the lender i region-specific indexes for climate extreme events across the four regions of interest, which is defined as follows:

$$Extreme\ regional - weighted\ impact\ costs_{i,k,t} =$$

$$= Extreme\ regional\ impact\ costs\ _{k,t} \times \frac{Lender\ regional\ amount_{i,k,t}}{Lender\ market\ amount_{i,t}}, \tag{13}$$

Other measures

In our empirical analysis we aim to explain the variations in systemic risk among banks. For this purpose, we employ a measure of systemic risk developed by Acharya et al. (2017) and Brownlees and Engle (2017). The bank-level systemic risk measure, *SRISK*, is defined as:

$$SRISK = E\ (k(D + MV) - MV \mid Crisis) =$$

$$= kD - (1-k)(1-LRMES)MV, \tag{14}$$

where k is the regulatory capital requirement, D is the book value of debt which is calculated as the difference between the book value of assets and the book value of equity and does not change during the crisis period, $LRMES$ (Long-Run Marginal Expected Shortfall) is the expected fractional loss in a firm's equity when the market index declines by more than 40% over a six-months period; and MV serves as a proxy for the firm's size, measured by its current market capitalization.

The other variables we include in the analysis are those used in the literature to explain variations in systemic risk related to banks' syndicated loan activities (Cai et al., 2018). For instance, based on Sina et al. (2025), we incorporate the monthly Eigenvector centrality measure for each lender in the syndicated loans market as a proxy for market interconnectedness. This is a widely recognised centrality metric based on network analysis (Larcker et al., 2013; Hochberg et al., 2007; Houston et al., 2018; Asgharian et al., 2022). We also introduce a proxy for the syndication risk associated with leveraged and covenant-lite loans, as defined by Sina et al. (2025). Specifically, the measure $SN\_RISK_{i,t}^{Lev\&CovLite}$ for each lender i in month t is defined as:

$$SN\_RISK_{i,t}^{Lev\&CovLite} = \frac{Lev_{i,t} + Lev\&CovLite_{i,t} + CovLite_{i,t}}{Lev_t + Lev\&CovLite_t + CovLite_t}, \tag{15}$$

where $Lev_{i,t}$ represents the issued amount of leveraged but not covenant-lite loans, $CovLite_{i,t}$ is the issued amount of covenant-lite but not leveraged loans, and $Lev\&CovLite_{i,t}$ denotes the amount of loans that are both leveraged and covenant-lite. Additional control variables, consistent with the literature on syndicated loans and systemic risk (Cai et al., 2018; Sina et al., 2025), include the following. Lender size, measured by total assets in billions of dollars[19], is sourced from Orbis. Market size of the syndicated loan market, in billions of dollars, is based on the calculations in Sina et al. (2025), as is the bank's market share of the syndicated loan market. Finally, one-period lagged SRISK is included to account for the persistence of systemic risk over time.

4.2.3. Model

To investigate the relationship between the systemic risk of U.S. lenders in the syndicated loan market and climate risks, we introduce the following econometric model, which incorporates several climate-based variables in addition to control variables drawn from the literature on syndicated loans and systemic risk:

$$\Delta SRISK_{i,t} = \alpha + \beta_1 (Environmentally\_friendly\_index_{i,t-1})$$
$$+\beta_2 (Western\ temperature\ regional - weighted\ index_{i,t-1})$$
$$+\beta_3 (Western\ precipitation\ regional - weighted\ index_{i,t-1})$$
$$+\beta_4 (Eastern\ temperature\ regional - weighted\ index_{i,t-1})$$
$$+\beta_5 (Eastern\ precipitation\ regional - weighted\ index_{i,t-1})$$
$$+\beta_6 (Central\ temperature\ regional - weighted\ index_{i,t-1})$$
$$+\beta_7 (Central\ temperature\ regional - weighted\ index_{i,t-1})$$
$$+\beta_8 (Southern\ temperature\ regional - weighted\ index_{i,t-1})$$
$$+\beta_9 (Southern\ temperature\ regional - weighted\ index_{i,t-1})$$
$$+\beta_{10} (Western\ \mathrm{PDSI} - weighted\ index_{i,t-1})$$
$$+\beta_{11} (Eastern\ \mathrm{PDSI} - weighted\ index_{i,t-1})$$
$$+\beta_{12} (Central\ \mathrm{PDSI} - weighted\ index_{i,t-1})$$
$$+\beta_8 (Southern\ PDSI - weighted\ index_{i,t-1})$$
$$+\beta_9 (Western\ extreme - weighted\ impact\ cost_{i,t-1})$$
$$+\beta_{10} (Eastern\ extreme - weighted\ impact\ cost_{i,t-1})$$
$$+\beta_{11} (Central\ extreme - weighted\ impact\ cost_{i,t-1})$$
$$+\beta_{12} (Southern\ extreme - weighted\ impact\ cost_{i,t-1})$$
$$+\beta_{10} (SN\_RISK_{i,t-1} * USRecession_t)$$
$$+\beta_{11} (SN\_RISK_{i,t-1} * USNon - Recession_t)$$

$$
\begin{aligned}
&+\beta_{12}\left(Interconnectedness_{i,t-1} * USRecession_t\right)\\
&+\beta_{13}\left(Interconnectedness_{i,t-1} * USNon-Recession_t\right)\\
&+\beta_{14}(TotalAssets_{i,t-1})\\
&+\beta_{15}(MarketSize_{i,t-1})\\
&+\beta_{16}\left(LaggedSRISK_{i,t-1}\right) + FixedEffects_i + \varepsilon_{i,t}
\end{aligned}
\tag{16}
$$

We extend this model by incorporating various specifications to capture both the distinct and combined effects of firm-specific and regional-based physical climate risks. To address the non-stationarity of *SRISK*, which occurs primarily during recessionary periods, we define our dependent variable as the first difference in *SRISK*, measured in billions of U.S. dollars (denoted as $\Delta SRISK$). Our key variables of interest include proxies for climate firms' environmental risks and climate physical risks. Specifically, the Green Lender Index $Green\_lender\_index_{i,t-1}$ serves as a proxy for banks' environmental portfolio risk, while the climate-based indices, including temperature and precipitation anomalies, the *PDSI*, and the costs associated with extreme events, are weighted according to lenders' regional share of syndicated loans to capture physical risks. We include commonly used control variables from the literature (Cai et al., 2018; Sina et al., 2025), all lagged by one month. Lenders' interconnectedness captures how banks are connected in the syndicated loan market and their potential influence on systemic risk. Total assets reflect bank size, since larger banks are usually more connected and may face higher systemic risk. A bank's market share and the overall market size capture its role and activity within the syndicated loan market. Finally, one-period lagged SRISK accounts for the persistence of systemic risk over time and helps isolate the effects of climate and lending variables. We also account for U.S. recessionary periods using a National Bureau of Economic Research (NBER) recession dummy. We control for unobserved heterogeneity among lenders by introducing bank fixed effects and clustering standard errors at the bank level. Additionally, we include the news-based indicators proposed in the literature by Engle et al. (2020), Ardia et al. (2023), and Faccini et al. (2023), which are detailed in Section 4.3.3.

Given the broad research question, we propose the following hypotheses for the four regions under study: Southern, Eastern, Central, and Western. These are based on each region's climate characteristics and banks' presence in syndicated loans. Focusing on the Southern Region, the main market for major U.S. banks and frequently affected by extreme climate events (Section 4.3), we propose the first hypothesis:

Hypothesis 1: The Southern Region, where extreme climate events are frequent and cause billions of dollars in losses, and where banks have a strong presence in syndicated loans, is positively associated with banks' systemic risk.

Following a similar approach, given that California (Western Region) is a key market for syndicated loans and that climate-related losses in this state have increased substantially, as shown in Section 4.3, we formulate the second hypothesis:

Hypothesis 2: Climate variables reflecting anomalies, droughts, and extreme events in the Western Region are more strongly associated with the systemic risk of banks that are heavily exposed to these regions through syndicated loans.

Finally, since the Southern, Eastern, and Western regions are the most important both in terms of U.S. syndicated loans and in terms of climate-related losses, we propose the third hypothesis:

Hypothesis 3: While in the Southern, Eastern, and Western regions banks' systemic risk is primarily associated with short-term climate anomalies, in the Central Region it is medium- to long-term drought conditions that play a dominant role. This likely reflects the structural importance of agriculture- and water-intensive activities in the Central area, where persistent droughts affect borrowers' balance sheets and creditworthiness over longer horizons rather than through transitory climate shocks.

4.3. Data

To conduct this study, we collected data from multiple sources covering climate information, syndicated loan data, banks' systemic risk measures, and other economic and financial control variables.[20] To build the final dataset for the empirical analysis we use a combination of automated and manual matching techniques.

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[20] We obtain systemic risk data for U.S. banks involved in syndicated loans from the V-Lab Systemic Risk Database. For each bank, we gather size information, measured by total assets on the balance sheet, from Thomson Reuters. Additionally, our control variables include

4.3.1. Syndicated loans data

We use U.S. syndicated loan variables previously developed in Sina et al. (2025), which are also utilized here as inputs for our analysis.[21] Table 4.2 presents the distribution of syndicated loan amounts issued by four major lenders—JPMorgan, Bank of America, Citi, and Wells Fargo—across various U.S. states (Panel A) and industrial sectors (Panel B) from 2000 to 2022. As shown, there is a significant concentration of syndicated loan issuance in specific sectors and states. Notably, the top three states in terms of syndicated loan amounts are Texas, California, and New York (Panel A of Table 4.2). In terms of industrial sectors (Panel B of Table 4.2), the following sectors are particularly prominent, collectively accounting for about 80% of the loan amounts for each bank: Manufacturing, Finance, Insurance & Real Estate, Services, and Transportation & Public Utilities. We integrate raw syndicated loan data with borrowers' environmental scores. This is done by matching borrower details, including names, headquarters locations, and identifier codes. We obtained annual environmental pillar scores for U.S. public companies from Thomson Reuters Refinitiv, with scores ranging from 0 to 100. A lower score indicates weaker environmental performance compared to the benchmark, while a higher score reflects a stronger commitment to environmental responsibility. Our database of syndicated loans, paired with borrowers' environmental scores, comprises 2,126 borrower-year observations across various sectors, as detailed in Panel A of Table 4.3. This analysis spans from 2003 to 2022, reflecting the absence of environmental pillar scores prior to 2003. While not every borrower in the U.S. syndicated loan market has corresponding environmental scores, the sector distribution closely mirrors the GDP distribution of the U.S. economy,[22] providing a valuable subset for analysis.

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indicators for recession and non-recession periods, provided by the National Bureau of Economic Research (NBER).

[21] To create the lending exposure measures for lenders in the U.S. syndicated loan market during the period 2000-2022, we utilize data sourced from Dealscan. For each lender in the syndicated market, we aggregate loan amounts at the parent company level. We adjust this dataset for mergers and acquisitions (M&As) that occurred in the financial sector during the sample period by merging it with the Thomson Reuters M&As database. This adjustment has been performed both automatically and manually.

[22] The industrial-based contribution to the U.S. GDP is detailed in the U.S. Bureau of Economic Analysis website, which can be accessed at the $https://www.bea.gov/itable/gdp-by-industry$.

Table 4.2: Distribution of lenders' syndicated loan amounts by industrial sectors and United States

This table shows the distribution of syndicated loan amounts issued by major lenders—JPMorgan, Bank of America, Citi, and Wells Fargo—across different U.S. states (Panel A) and industrial sectors (Panel B) for the period from 2000 to 2022.

Panel A. Share distribution across U.S. states

JPM			**Bank of America**			**Citi**			**Wells Fargo**		
Rank	U.S. state	Share	Rank	U.S. state	Share	Rank	U.S. state	Share	Rank	U.S. state	Share
1	New York	12.9%	1	Texas	11.9%	1	Texas	14.3%	1	Texas	14.4%
2	Texas	12.7%	2	California	11.8%	2	New York	14.0%	2	California	12.3%
3	California	8.0%	3	New York	10.3%	3	California	8.8%	3	New York	8.7%
4	Illinois	7.0%	4	Illinois	7.3%	4	Illinois	6.3%	4	Illinois	5.8%
5	New Jersey	4.6%	5	Massachusetts	4.5%	5	New Jersey	6.1%	5	Georgia	4.1%
6	Other	54.7%	6	Other	54.2%	6	Other	50.5%	6	Other	54.7%
	Total	*100%*		*Total*	*100%*		*Total*	*100%*		*Total*	*100%*

Panel B. Share distribution across industrial sectors

JPM			**Bank of America**			**Citi**			**Wells Fargo**		
Rank	Industrial sectors	Share	Rank	Industrial sectors	Share	Rank	Industrial sectors	Share	Rank	Industrial sectors	Share
1	Manufacturing	31.4%	1	Manufacturing	28.0%	1	Manufacturing	36.4%	1	Manufacturing	24.4%
2	Finance, Insurance & Real Estate	20.5%	2	Finance, Insurance & Real Estate	22.4%	2	Transportation & public utilities	19.8%	2	Finance, Insurance & Real Estate	22.4%
3	Services	16.5%	3	Services	16.6%	3	Finance, Insurance & Real Estate	17.9%	3	Services	15.8%
4	Transportation & Public Utilities	14.9%	4	Transportation & public utilities	14.3%	4	Services	12.8%	4	Transportation & public utilities	11.8%
5	Mining	5.8%	5	Retail trade	7.1%	5	Mining	6.1%	5	Retail trade	9.4%
6	Retail trade	5.4%	6	mining	4.3%	6	Retail trade	4.1%	6	mining	7.3%
7	Wholesale trade	3.3%	7	Wholesale trade	4.0%	7	Wholesale trade	1.6%	7	Wholesale trade	5.3%
8	Construction	0.9%	8	Construction	2.1%	8	Construction	0.6%	8	Construction	1.6%
9	Agriculture, Forestry, & Fishing	0.2%	9	Agriculture, Forestry, & Fishing	0.4%	9	Agriculture, Forestry, & Fishing	0.0%	9	Agriculture, Forestry, & Fishing	0.5%
	Total	*100%*		*Total*	*100%*		*Total*	*100%*		*Total*	*100%*

Notably, the Manufacturing sector has the largest representation in the dataset, with an average score of 45.30, indicating a moderate level of environmental performance. This suggests that sustainability initiatives are ongoing within this sector. The Transportation & Public Utilities sector follows closely with a mean score of 46.80, reflecting slightly stronger environmental performance compared to Manufacturing. In contrast, the Services sector and the Finance, Insurance & Real Estate sector show more concerning results, with the latter having the lowest mean score at 35.14. This suggests that financial institutions may not prioritize environmental considerations as much as firms in other sectors. Additionally, the Mining sector, which has a mean score of 37.46, is encountering significant challenges in transitioning its firms toward more environmentally friendly practices. The high score for Agriculture, Forestry, & Fishing (average 74.18) is influenced by the limited observations available (three). This underscores the need for greater transparency and information regarding environmental performance from firms in this sector. Overall, the data suggest significant disparities in environmental performance across sectors, with Manufacturing and Transportation leading, while Finance and Mining lagging behind. The considerable variability within each sector underscores the existence of both high and low performers, highlighting the urgent need for targeted strategies to enhance environmental outcomes across all industries.

Panel B of Table 4.3 reports the distribution of borrowers' environmental scores across U.S. states, revealing substantial regional heterogeneity. Minnesota records the highest mean score (54.89), suggesting comparatively strong environmental performance. New York (47.90) and New Jersey (47.14) follow, indicating a relatively robust commitment to environmental standards in these densely populated and economically active states. In contrast, Pennsylvania exhibits the lowest mean score (37.50), pointing to potential challenges in environmental practices. Among the states most active in syndicated loan issuance, Texas records the lowest average score (41.43), which likely reflects its industrial structure, heavily concentrated in energy-intensive and resource-extractive sectors that tend to show weaker environmental performance. California, another major hub for syndicated loans, presents a mean score of 43.81, suggesting both room for improvement and evidence of ongoing sustainability efforts. Finally, the "Other" category, encompassing a diverse set of states, shows a mean score of 36.65, underscoring that many borrowers operate with limited emphasis on environmental considerations.

Table 4.3: Environmental scores by industry and state in the United States

This table provides summary statistics of environmental scores for industrial sectors (Panel A) and states (Panel B) in the United States.

Panel A. Environmental scores of borrowers by industrial sectors

Industrial sectors	**N**	**Mean**	**SD**	**p10**	**p50**	**p90**
Manufacturing	880	45.30	26.34	8.22	46.29	81.02
Finance, Insurance & Real Estate	342	35.14	23.32	10.55	27.21	74.63
Transportation & Public Utilities	329	46.80	25.61	10.52	49.39	79.90
Services	204	40.74	26.02	4.87	38.62	77.06
Mining	152	37.46	26.01	4.13	38.73	71.40
Retail trade	135	42.68	27.58	6.58	39.50	81.11
Wholesale trade	56	37.82	22.99	4.69	35.97	67.12
Construction	25	32.64	21.98	3.78	30.16	70.32
Agriculture, Forestry, & Fishing	3	74.18	17.72	53.73	83.70	85.09

Panel B. Environmental scores of borrowers by state

United States	**N**	**Mean**	**SD**	**p10**	**p50**	**p90**
Texas	197	41.43	25.85	7.47	38.83	78.55
California	197	43.81	25.44	7.85	43.61	75.89
Illinois	182	45.56	25.14	12.73	44.14	79.88
New York	181	47.90	25.88	11.62	47.60	83.68
Ohio	103	41.45	22.95	8.35	41.60	70.31
Pennsylvania	90	37.50	22.81	9.48	31.59	75.50
Massachusetts	82	42.13	26.28	6.56	40.41	77.48
Minnesota	72	54.89	27.64	9.74	59.02	87.97
Georgia	71	39.98	24.76	3.44	40.72	75.14
New Jersey	70	47.14	27.00	13.05	41.68	86.36
Other	*861*	*36.65*	*21.91*	*13.36*	*33.97*	*62.83*

4.3.2. NCEI-based data

To incorporate climate physical risk data into our dataset, we collect various variables. Specifically, we gather regional monthly data on climate temperatures and precipitation from 2000 to 2022, sourced from the National Centers for Environmental Information (NCEI), available at the following link: https://www.ncei.noaa.gov/access/monitoring/climate-at-a-glance/regional/time-series. Table 4.4 summarizes temperature data, precipitation data, and the Palmer Drought Severity Index for the four regions[23]: Western, Eastern, Central, and Southern. We also include details about the main state in each region regarding the amount of syndicated loans. Looking at the temperature statistics in Panel A of Table 4.4, the Southern region has the highest average temperature at 63.33°F, indicating it is warmer than the other regions. This is especially true for Texas, which has an average temperature of 66.04°F. In terms of temperature anomalies, the Western region has a notable mean anomaly of +1.78°F, with California showing the highest anomaly at +1.97°F compared to the regional average. This, combined with the region's strong winds, makes California particularly vulnerable to extreme wildfire events. Regarding precipitation, Panel B of Table 4.4 highlights that the Eastern region has the highest levels, measuring 3.87 mm of rainfall, along with a positive anomaly of 0.26. These short-term anomalies are also influenced by tropical cyclones that affect this area throughout the year. In the Eastern region, New York has slightly lower average rainfall at 3.71 mm, but it experiences a higher rainfall anomaly of +0.36 mm. In Panel C of Table 4.4, we provide summary statistics for the Palmer Drought Severity Index (PDSI). The Western region stands out because it has much lower PDSI values and anomalies compared to the other regions. The average PDSI value for the Western region is -1.83, indicating drier and more severe drought conditions. California, which is part of this region, has a PDSI value of -1.78, highlighting the tough drought situation that characterize this area. The Southern region also shows signs of drought stress, with an average PDSI value of -0.61, while Texas has an even lower value of -0.90.

[23] The detailed list of the States associated with each region is available at the following link: https://www.ncei.noaa.gov/access/monitoring/reference-maps/nws-regions

Table 4.4: Climate risk variables

This table presents climate risk variables categorized by National Weather Service (NWS) regions in the United States. Panel A concentrates on temperature, Panel B addresses precipitation, and Panel C provides key statistics for the Palmer Drought Severity Index (PDSI).

Panel A. Temperature value and anomaly

NWS regions	Variable	Mean	SD	10th	50th	95th
Eastern	Temperature value (F°)	52.35	15.50	31.65	52.58	73.70
of which New York		*46.34*	*17.12*	*23.75*	*46.30*	*70.10*
Western		51.12	14.13	33.35	49.90	72.25
of which California		*59.35*	*11.86*	*44.45*	*58.15*	*77.55*
Central		47.86	17.92	22.70	48.33	72.80
of which Illinois		*52.82*	*17.60*	*28.95*	*54.13*	*75.65*
Southern		63.33	13.17	45.35	63.60	81.20
of which Texas		*66.04*	*13.23*	*47.90*	*66.45*	*84.10*
Eastern	Temperature anomaly	1.64	2.89	-1.85	1.50	6.35
of which New York		*1.84*	*3.39*	*-1.90*	*1.60*	*7.60*
Western		1.78	2.37	-1.15	1.78	5.65
of which California		*1.97*	*2.38*	*-1.10*	*2.10*	*5.85*
Central		1.48	3.22	-2.50	1.50	6.90
of which Illinois		*1.19*	*3.78*	*-3.05*	*1.15*	*7.20*
Southern		1.27	2.28	-1.40	1.08	5.25
of which Texas		*1.40*	*2.59*	*-1.60*	*1.20*	*5.65*

Panel B. Precipitation value and anomaly

NWS regions	Variable	Mean	SD	10th	50th	95th
Eastern	Precipitation value (mm)	3.87	1.13	2.35	3.90	5.86
of which New York		*3.71*	*1.34*	*2.13*	*3.49*	*6.08*
Western		1.66	0.87	0.71	1.49	3.52
of which California		*1.71*	*1.98*	*0.90*	*0.87*	*6.19*
Central		2.38	1.04	1.04	2.27	4.11
of which Illinois		*3.44*	*1.64*	*1.48*	*3.30*	*6.77*
Southern		3.19	1.09	1.85	3.09	5.19
of which Texas		*2.33*	*1.43*	*0.74*	*2.15*	*5.33*
Eastern	Precipitation anomaly	0.26	1.03	-1.01	0.22	2.17
of which New York		*0.36*	*1.24*	*-1.11*	*0.25*	*2.60*
Western		-0.08	0.64	-0.85	-0.16	1.10
of which California		*-0.16*	*1.46*	*-1.98*	*-0.14*	*2.54*
Central		0.14	0.64	-0.62	0.08	1.25
of which Illinois		*0.31*	*1.43*	*-1.35*	*0.14*	*3.21*
Southern		0.09	1.00	-1.09	-0.07	1.97
of which Texas		*0.08*	*1.32*	*-1.38*	*-0.22*	*2.81*

(Table 4.4 - continues in the next page)

(Table 4.4 - continued)

Panel C. Palmer Drought Severity Index (PDSI)

NWS regions	Variable	N.	Mean	SD	50th	95th
Eastern	PDSI value	276	0.71	2.21	-1.96	0.88
of which New York		*276*	*1.26*	*1.94*	*-1.53*	*1.49*
Western		276	-1.83	2.43	-4.30	-2.49
of which California		*276*	*-1.78*	*2.63*	*-4.85*	*-2.30*
Central		276	0.99	2.38	-1.47	0.63
of which Illinois		*276*	*1.26*	*2.25*	*-1.82*	*1.55*
Southern		276	-0.61	2.84	-5.08	-0.37
of which Texas		*276*	*-0.90*	*3.11*	*-4.48*	*-1.23*
Eastern	PDSI anomaly	276	0.61	2.21	-2.06	0.80
of which New York		*276*	*1.28*	*1.94*	*-1.52*	*1.45*
Western		276	-2.06	2.43	-4.49	-2.73
of which California		*276*	*-1.79*	*2.65*	*-4.89*	*-2.26*
Central		276	0.59	2.38	-1.91	0.21
of which Illinois		*276*	*1.23*	*2.25*	*-1.92*	*1.52*
Southern		276	-0.72	2.84	-5.16	-0.52
of which Texas		*276*	*-0.85*	*3.12*	*-4.52*	*-1.22*

Table 4.5 provides an overview of the financial impact of extreme weather events in the United States across three sub-periods. Panel A presents incidence costs by region, Panel B outlines the percentage contributions of each event type to regional total expenses, and Panel C highlights the percentage contributions of each event type to overall U.S. expenses. From 1999 to 2022, the Eastern Region suffered the most significant financial impact from tropical cyclones, peaking at $280 billion between 2013 and 2022. The Southern Region followed closely, with costs reaching $246 billion during the same period. Together, tropical cyclones in these two regions account for approximately 65% of the total costs related to extreme events in the U.S. In the Western Region, wildfire costs escalated to $75 billion from 2013 to 2022, representing 9.1% of total U.S. costs. Although this percentage may seem small, the cost of wildfires in the Western Region has increased by over 1000% in the last 20 years, highlighting a growing threat to both the environment and the economy, particularly in California, the most affected state. The Central Region's expenses were primarily driven by severe storms, totalling $41 billion from 2013 to 2022, which accounts for 5.0% of the total extreme weather costs in the U.S.

Table 4.5: Total costs of extreme events

This table shows the financial impact of extreme weather events in the United States across three sub-periods, with Panel A showing incidence costs by region, Panel B detailing the percentage contributions of each event type to regional total expenses, and Panel C presenting the percentage contributions of each event type to the total expenses for the U.S. as a whole.

Panel A. Costs incidence of extreme events (Billion-dollar) in the United States

Year	Region	Drought	Flooding	Freeze	Severe Storm	Tropical Cyclone	Wildfire	Winter storm
1999-2006	Eastern	-	4	-	4	145	1	3
	Western	-	-	-	-	-	6	-
	Central	-	-	-	20	1	-	1
	Southern	-	-	-	12	226	1	1
2007-2012	Eastern	1	4	1	22	105	1	3
	Western	2	-	2	1	-	4	-
	Central	1	8	1	32	7	-	1
	Southern	1	3	1	29	47	3	1
2013-2022	Eastern	1	3	1	26	280	0	9
	Western	-	3	-	0	-	75	-
	Central	-	10	-	41	1	2	3
	Southern	-	31	-	62	246	-	24

Panel B. Cost contribution of each extreme event (Billion-dollar) relative to the total expenses of all extreme events at the regional level

Year	Region	Drought	Flooding	Freeze	Severe Storm	Tropical Cyclone	Wildfire	Winter storm
1999-2006	Eastern	-	2.4%	-	2.8%	92.6%	-	1.9%
	Western	-	-	-	-	-	100.0%	-
	Central	-	-	-	91.4%	5.4%	-	3.2%
	Southern	-	-	-	4.9%	94.4%	-	0.5%
2007-2012	Eastern	0.6%	2.7%	0.6%	15.9%	77.4%	-	2.4%
	Western	23.6%	-	23.6%	7.9%	-	44.9%	-
	Central	2.8%	15.8%	2.8%	64.2%	13.1%	-	1.4%
	Southern	1.0%	3.5%	1.0%	34.2%	56.5%	3.0%	1.0%
2013-2022	Eastern	0.4%	0.9%	0.4%	8.1%	87.4%	0.1%	2.7%
	Western	-	3.8%	-	0.5%	-	95.6%	-
	Central	-	18.2%	-	72.6%	1.3%	3.0%	4.8%
	Southern	-	8.6%	-	17.1%	67.8%	-	6.5%

(Table 4.5 - continues in the next page)

(Table 4.5 - continued)

Panel C. Cost contribution of each extreme events (Billion-dollar) relative to the total expenses of all extreme events in the United States

Year	Region	Drought	Flooding	Freeze	Severe Storm	Tropical Cyclone	Wildfire	Winter storm
1999-2006	Eastern	-	0.9%	-	1.0%	34.1%	0.2%	0.7%
	Western	-	-	-	-	-	1.4%	-
	Central	-	-	-	4.8%	0.3%	-	0.2%
	Southern	-	-	-	2.8%	53.4%	0.1%	0.3%
2007-2012	Eastern	0.3%	1.3%	0.3%	7.7%	37.6%	0.2%	1.2%
	Western	0.8%	-	0.8%	0.3%	-	1.4%	-
	Central	0.5%	2.9%	0.5%	11.6%	2.4%	-	0.3%
	Southern	0.3%	1.0%	0.3%	10.3%	17.0%	0.9%	0.3%
2013-2022	Eastern	0.1%	0.3%	0.1%	3.2%	34.3%	0.0%	1.1%
	Western	-	0.4%	-	-	-	9.1%	-
	Central	-	1.2%	-	5.0%	0.1%	0.2%	0.3%
	Southern	-	3.8%	-	7.6%	30.1%	-	2.9%

4.3.3. Literature-based data

To improve our analysis of climate change's influence on systemic risk using non-self-reported measures, we incorporate various risk indicators from the literature. We present a proxy for firms' climate change exposure risk (Sautner et al., 2023), which is the CCExposure metric.[24] It quantifies the relative frequency of bigrams related to climate change found in earnings conference call transcripts. The metric is calculated quarterly and encompasses the entire duration of our empirical analysis (from 2000 to 2022) by counting the relevant bigrams and dividing that number by the total count of bigrams in the transcripts. We draw on two variables from Engle et al. (2020). First, the Wall Street Journal (WSJ) Climate Change News Index measures climate change coverage in the WSJ by comparing its content to a defined set of climate-related terms, as detailed in the study "Hedging Climate Change News." Second, the Crimson Hexagon (CH) Negative Climate Change News Index specifically targets negative climate news. Together, these indices provide valuable insights into market perceptions of climate change, reflecting both positive and negative elements of news coverage. Data are

[24] The metric is available at the following link: https://osf.io/fd6jq/files/osfstorage

gathered monthly, extending through June 2017 for the WSJ index and May 2018 for the second index.[25]

To account for unexpected increases in climate change concerns, we use the Media Climate Change Concerns Index from Ardia et al. (2023)[26], recorded monthly from January 2003 to August 2022. The index measures the shift in public concerns by analysing news articles with risk and sentiment lexicons. Additionally, we construct a monthly measure by averaging the daily climate risk indicators developed by Faccini et al. (2023) over each month.[27] These metrics are based on textual and narrative analyses of Reuters' coverage of climate policy actions and discussions. The indices cover themes including natural disasters, global warming, international summits, and U.S. climate policy. In particular, the U.S. climate policy variable captures transition risk from U.S. political and regulatory actions, based on LDA-applied news articles mentioning "climate change" or "global warming," and aggregating topic shares from state- and federal-level policy discussions. This variable reflects the perceived likelihood and intensity of future climate-related regulation, which may affect firms operationally, strategically, and financially. By capturing media attention to climate policy debates, it serves as a forward-looking proxy for regulatory developments that could influence firm behaviour and impact financial markets.

4.4. Results

Our primary regression model explores the relationship between systemic risk in U.S. banks and climate-adjusted lending variables, which act as proxies for both banks' portfolio environmental risk and physical climate risks. Table 4.6 presents the results from our baseline regression model. Across model specifications [1], [3], [4], and [7], we find a consistent negative and statistically significant effect associated with the $Environmentally\_friendly\_index_{i,t}$. This indicates that banks engaged in financing environmentally-friendly projects within the U.S.

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[25] Both indices are available at the following link: https://drive.google.com/file/d/1pCHmcebmOwrVCFim78ALhB51c3h1qt2T/view?pli=1
[26] The index is available at the following link: https://sentometrics-research.com/
[27] The indexes are available at the following link: https://docs.google.com/spreadsheets/d/1JW7l_ZLCsPm7wPOrSaEZzMedZJ7M2opK/edit?pli=1&gid=793134818#gid=793134818

syndicated market tend to experience lower levels of systemic risk. This effect is both statistically significant and economically substantial, reflecting a reduction in systemic risk variability of approximately 6% associated with the $Environmentally\_friendly\_index_{i,t}$. By supporting sustainable initiatives, these banks may enhance their stability and resilience against broader financial uncertainties, positioning themselves more favorably in a market increasingly influenced by environmental considerations.

The findings in Table 4.6 show a clear connection between climate-related factors and how banks make lending decisions, especially across different regions. The data indicates that climate risks, whether from short-term weather changes or the costs of extreme events, are linked to higher systemic risk for banks. This means that the market sees these physical risks as harmful, particularly in areas that face environmental challenges. For instance, the Southern region, which is important for syndicated markets, has the highest average temperatures and also deals with extreme events that make up about one-third of total costs in the U.S. As shown in Table 4.6, the results for the Southern region are consistent with our first hypothesis (discussed in Section 4.2.3). Hypothesis 1 states that the Southern region, where extreme climate events are frequent and generate substantial economic losses, and where banks have a strong presence in the syndicated loan market, is positively associated with banks' systemic risk. In line with this hypothesis, we find that the variable capturing losses caused by extreme climate events is positive and statistically significant at the 5% level. Moreover, the variable measuring short-term temperature anomalies displays a positive and highly statistically significant coefficient at the 1% level across all model specifications. Taken together, these results provide support for Hypothesis 1, suggesting that banks' exposure to the Southern region, which is highly sensitive to short-term climate shocks and experiences billions in losses caused by extreme events, is associated with higher cross-sectional variation in systemic risk.

Our second hypothesis states that climate variables reflecting anomalies, droughts, and extreme events in the Western region are more strongly associated with the systemic risk of banks that are heavily exposed to these areas through syndicated loans. This hypothesis is mainly motivated by the increasing relevance of extreme climate events in California, where wildfire-related costs have increased by over 1,000% over the past 20 years. Our results provide partial support for this hypothesis. The variable capturing extreme event–weighted impact costs in the Western region is positive and statistically significant across all model specifications. However, the variables capturing climate anomalies do not show robust significance across specifications [2] to [11] of Table 4.6. Overall, the evidence suggests that climate variables related to extreme events in the Western region are associated with higher systemic risk. At the same time, the results do not allow for a clear conclusion regarding the role of short-term climate anomalies and drought-related conditions in this region.

Our Hypothesis 3 suggests that banks' systemic risk in the Southern, Eastern, and Western regions is mainly linked to short-term climate anomalies, while in the Central region medium- to long-term drought conditions play a more important role due to the relevance of agriculture and water-intensive activities. The results provide partial support for this hypothesis. Short-term precipitation anomalies in the Eastern region and temperature anomalies in the Southern region are statistically significant, while the evidence for the Western region is not robust in the main results. However, the results reported in Table 4.6 indicate that medium- to long-term drought conditions in the Central region are associated with higher systemic risk, supporting our third hypothesis for this area.

In addition to climate-risk factors, our regression models include control variables from previous studies that explain differences in lenders' systemic risk, and our results are consistent with earlier findings (Cai et al., 2018; Sina et al., 2025). We find a positive relationship between banks' $Interconnectedness * US\ Recession$, and systemic risk. This indicates that banks that are more connected to others in the network tend to be associated with higher systemic risk during economic downturns. Similarly, banks with portfolios concentrated in leveraged and covenant-lite loans, captured by $SN - RISK * US\ Recession$, are associated with higher systemic risk, as these riskier loans make banks more sensitive to market stress and amplify their potential impact on the financial system. Total assets are positively associated with systemic risk as well, consistent with Cai et al. (2018), Laeven et al. (2016), Sedunov (2016), and Sina et al. (2025), suggesting that larger banks are more systemically important, and their failure or distress could have broader repercussions. Overall, these results confirm that structural characteristics of banks, including interconnectedness, portfolio composition, and size, significantly influence systemic risk, especially during periods of economic stress. Overall, our findings in Table 4.6 suggest that encouraging eco-friendly lending practices could lower systemic risk in the banking sector. Banks that contribute most to the “green” market can enhance their reputation and attract environmentally conscious clients, aligning with sustainable finance regulations. However, lending to areas vulnerable to climate-related risks is associated with higher systemic risk, especially during extreme weather and changes in temperature and rainfall. Even with the increasing focus on sustainability, our results suggest that there are still concerns about banks' ability to manage physical climate risks effectively.

Table 4.7 presents the analysis of the link between systemic risk and climate change risk, using a set of literature-based variables developed by Engle et al., 2020; Ardia et al., 2023; Sautner et al., 2023; Faccini et al., 2023. Model [1] shows that the CCExposure_index adjusted for banks’ syndicated loan exposures (as described in Section 4.3.3) is significantly associated with systemic risk. However, this significance disappears in Model [2] when the environmentally-friendly index is included, indicating potential redundancy in the information captured by the two measures. In fact, the two measures show a correlation of approximately 50%, highly due to their shared dependence on loan amounts. Since both account for banks’ exposure to borrowers weighted by loan size, the environmentally-friendly index naturally overlaps with the CCExposure_index. As a result, the borrower environmental score captures much of the information embedded in CCExposure. The results from models [2] and [3] in Table 4.7 indicate that neither of the climate change variables introduced by Engle et al. (2020), which are based on news data, demonstrate any relationship with systemic risk. It is important to consider that these findings may be influenced by the limited number of observations, which restricts a more detailed analysis beyond 2017 for the Wall Street Journal index and 2018 for the Crimson Hexagon (CH) Negative Climate Change News Index. Similarly, the Media Climate Change Concerns Index presented in model [5] of Table 4.6 does not show a significant association with systemic risk. Overall, indices based on market news do not show a significant relationship with banks’ systemic risk, likely because short-term anomalies and extreme climate events capture most of the effect. Market-based indicators tend to reflect immediate reactions, while systemic risk is more strongly driven by the direct financial impacts of these events on banks’ exposures.

Table 4.6: Relationship between systemic risk and climate risks

This table displays the results of panel regressions based on Equation (16), with the dependent variable being the ΔSRISK of U.S. lenders. The main independent variables are the one-month lagged climate-related risk variables, which serve as proxies for lenders' portfolio environmental risks and climate physical risk, as detailed in Section 4.2.1. Additional independent variables include lagged proxies of interconnectedness derived from syndicated loan networks, along with the syndication risk measure of leveraged and covenant-lite loans, as detailed in Section 4.2.2. The USRECD indicator, based on NBER data, identifies U.S. recession periods, taking a value of 1 during recessions and 0 otherwise, while its complement indicates non-recession periods. Other lagged control variables include the lender's total assets (in billions of dollars), market share in the U.S. syndicated loan market (as a percentage), the overall size of the syndicated loan market (in billions of dollars), and the lagged SRISK. All regressions are adjusted for fixed effects of the banks. The sample period covers monthly observations from 2004 to 2022. At the bottom of the table, information is provided on the number of observations, fixed effects, number of clusters (i.e., banks), and adjusted R-squared values. Significance levels are indicated by *, **, and ***, representing coefficients that are significantly different from zero at the 10%, 5%, and 1% levels,

Dependent variable: ΔSRISK	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)	(9)	(10)	(11)
Environmentally_Friendly_Index	-8.337**		-8.217**	-8.213**		-8.093**			-8.213**		-8.097**
	(3.635)		(3.644)	(3.643)		(3.655)			(3.645)		(3.655)
Western temperature−weighted anomaly index		0.328	0.323			0.328	0.333	0.440*	0.433*	0.453*	0.446*
		(0.208)	(0.212)			(0.209)	(0.206)	(0.252)	(0.255)	(0.250)	(0.253)
Western precipitation−weighted anomaly index		0.586	0.602			0.412	0.392	0.226	0.247	0.032	0.056
		(0.377)	(0.370)			(0.386)	(0.394)	(0.402)	(0.397)	(0.413)	(0.406)
Eastern temperature−weighted anomaly index		0.069	0.062			0.057	0.064	0.088*	0.081	0.078	0.071
		(0.049)	(0.050)			(0.050)	(0.049)	(0.049)	(0.050)	-0.049	(0.050)
Eastern precipitation−weighted anomaly index		0.326*	0.325*			0.377**	0.378**	0.344*	0.345*	0.382**	0.383**
		(0.170)	(0.168)			(0.174)	(0.175)	(0.181)	(0.180)	(0.185)	(0.184)
Central temperature−weighted anomaly index		0.065	0.062			0.048	0.050	0.034	0.031	0.025	0.022
		(0.114)	(0.113)			(0.113)	(0.114)	(0.108)	(0.106)	(0.108)	(0.107)
Central precipitation−weighted anomaly index		-0.252	-0.243			-0.286	-0.300	-0.453	-0.446	-0.426	-0.416
		(0.347)	(0.358)			(0.373)	(0.362)	(0.357)	(0.369)	(0.364)	(0.375)
Southern temperature−weighted anomaly index		0.153***	0.151***			0.156***	0.158***	0.156***	0.154***	0.157***	0.155***
		(0.050)	(0.050)			(0.050)	(0.050)	(0.048)	(0.047)	(0.048)	(0.048)
Southern precipitation−weighted anomaly index		-0.365	-0.367			-0.316	-0.313	-0.350	-0.350	-0.291	-0.292
		(0.245)	(0.247)			(0.247)	(0.244)	(0.235)	(0.237)	(0.231)	(0.234)
Western PDSI−weighted								0.264	0.259	0.288*	0.284*
								(0.162)	(0.162)	(0.167)	(0.166)
Eastern PDSI−weighted								-0.049	-0.053	-0.001	-0.005
								(0.080)	(0.080)	(0.090)	(0.090)
Central PDSI−weighted								0.191**	0.193**	0.156*	0.160**
								(0.074)	(0.073)	(0.080)	(0.079)
Southern PDSI−weighted								0.034	0.030	0.002	-0.001
								(0.059)	(0.060)	(0.058)	(0.059)

(Table 4.6 - continues in the next page)

(Table 4.6 - continued)

Dependent variable: ΔSRISK	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)	(9)	(10)	(11)
Western extreme−weighted impact cost				0.665**	0.671**	0.674**	0.681**			0.655**	0.646**
				(0.303)	(0.304)	(0.308)	(0.309)			(0.322)	(0.321)
Eastern extreme−weighted impact cost				0.374	0.386	0.377	0.390			0.411	0.398
				(0.527)	(0.523)	(0.533)	(0.530)			(0.540)	(0.543)
Central extreme−weighted impact cost				-0.154	-0.127	-0.143	-0.114			-0.281	-0.310
				(0.448)	(0.452)	(0.457)	(0.461)			(0.493)	(0.490)
Southern extreme−weighted impact cost				1.823**	1.850**	1.805**	1.829**			1.751**	1.730**
				(0.741)	(0.747)	(0.750)	(0.755)			(0.741)	(0.735)
Centrality × U.S. Recession	0.175**	0.179**	0.182**	0.167**	0.164**	0.173**	0.171**	0.177**	0.180**	0.169**	0.172**
	(0.072)	(0.073)	(0.072)	(0.076)	(0.076)	(0.076)	(0.077)	(0.073)	(0.072)	(0.077)	(0.077)
Centrality × U.S. Non-recession	-0.006	-0.002	-0.000	0.002	0.001	0.008	0.006	-0.003	-0.001	0.006	0.007
	(0.034)	(0.034)	(0.034)	(0.034)	(0.035)	(0.034)	(0.034)	(0.035)	(0.034)	(0.035)	(0.034)
$SN\_RISK^{Lev\&CovLite}$ × U.S. Recession	0.719***	0.710***	0.715***	0.730***	0.726***	0.727***	0.722***	0.714***	0.718***	0.725***	0.730***
	(0.196)	(0.204)	(0.196)	(0.202)	(0.209)	(0.203)	(0.210)	(0.205)	(0.197)	(0.211)	(0.204)
$SN\_RISK^{Lev\&CovLite}$ × U.S. Non-Recession	-0.094	-0.096	-0.092	-0.097	-0.101	-0.095	-0.099	-0.093	-0.090	-0.097	-0.093
	(0.119)	(0.123)	(0.120)	(0.119)	(0.122)	(0.120)	(0.122)	(0.124)	(0.121)	(0.123)	(0.121)
Total Assets (B$)	0.003***	0.003***	0.003***	0.003***	0.003***	0.003***	0.003***	0.003***	0.003***	0.003***	0.003***
	(0.000)	(0.000)	(0.000)	(0.000)	(0.000)	(0.000)	(0.000)	(0.000)	(0.000)	(0.000)	(0.000)
Constant	-1.868***	-2.184***	-2.006***	-2.660***	-2.851***	-2.802***	-2.996***	-2.213***	-2.035***	-2.971***	-2.777***
	(0.640)	(0.576)	(0.630)	(0.823)	(0.793)	(0.818)	(0.789)	(0.584)	(0.639)	(0.802)	(0.831)
Control variables	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes
Observations	4,334	4,334	4,334	4,334	4,334	4,334	4,334	4,334	4,334	4,334	4,334
Financial Institution FE	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes
Clusters	61	61	61	61	61	61	61	61	61	61	61
Adj. R^2	0.083	0.083	0.084	0.085	0.084	0.086	0.085	0.083	0.085	0.085	0.087

In contrast, models [6] and [7] of Table 4.7 show a positive and statistically significant relationship between U.S. climate policy and international summits. Our results suggest that U.S. systemic risk tends to rise after periods of increased media attention to new climate policies and, with a 10% significance level, following international climate summits. This may be because such initiatives often involve regulatory interventions and commitments to reduce emissions, which are government actions that, while aimed at supporting the transition to a greener economy, introduce short-term uncertainty. Although the intention behind climate policies and summits is to improve long-term investor confidence and financial stability, the process of implementation can create transitional stress. Regulatory uncertainty, unclear timelines, and varying speeds of adoption may contribute to market-wide risk, especially during the early phases of policy rollout. For banks, these uncertainties may lead to challenges in portfolio adjustments and credit risk management. In particular, banks exposed to environmentally risky borrowers may face greater risks from climate regulations, fines, or reputational damage. Rather than reducing systemic risk, these transition dynamics appear to introduce new vulnerabilities into the financial system in the short term. These complexities may hinder risk management and lead to unintended effects, increasing systemic fragility in the short term. Furthermore, because the U.S. climate policy factor captures near-term transition risks, such as regulatory changes and political appointments, its impact may be amplified by political risk, which can alter the direction or pace of climate policy, adding further uncertainty for markets.

Our results show a clear association between areas more affected by climate change and banks' systemic risk. This is especially true in regions where banks hold a large share of syndicated loans. These findings reflect correlations between the variables and should not be seen as causal effects. For example, banks with stronger capital, careful risk management, or conservative risk policies may both lend more to environmentally-friendly projects and have lower systemic risk. Similarly, regional climate factors may be linked to local economic conditions or to the type of banks operating there. This means that part of the association could be due to differences in bank quality or portfolio composition. Overall, our results show meaningful patterns that highlight how banks' lending choices and regional climate exposures relate to systemic risk. Our robustness checks support the consistency of these associations.

Future research could use experimental designs or special statistical tools to test for causal effects.

Table 4.7: Examining the connection between systemic risk and climate change risk through variables identified in existing literature (Engle et al., 2020; Ardia et al., 2022; Faccini et al., 2023; Sautner et al., 2023)

This table displays the results of panel regressions based on Equation (16), with the dependent variable being the ΔSRISK of U.S. lenders. The primary independent variables are the climate change risk variables developed by Engle et al. (2020), Ardia et al. (2022), Sautner et al. (2023), and Faccini et al. (2023), as outlined in Section 3.5.3. Additional variables include one-month lagged climate-related risk factors, which act as proxies for lenders' portfolio environmental risks and climate physical risks, as described in Section 4.2.1. Moreover, the model incorporates lagged proxies of interconnectedness derived from syndicated loan networks, along with a syndication risk measure for leveraged and covenant-lite loans, detailed in Section 4.2.2. The USRECD indicator, based on NBER data, identifies U.S. recession periods, taking a value of 1 during recessions and 0 otherwise, while its complement indicates non-recession periods. Other lagged control variables include the lender's total assets (in billions of dollars), market share in the U.S. syndicated loan market (as a percentage), the overall size of the syndicated loan market (in billions of dollars), and the lagged SRISK. All regressions are adjusted for the fixed effects of the banks. The sample period spans monthly observations from 2004 to 2022. At the bottom of the table, details are provided regarding the number of observations, fixed effects, number of clusters (i.e., banks), and adjusted R-squared values. Significance levels are indicated by *, **, and ***, denoting coefficients that are significantly different from zero at the 10%, 5%, and 1% levels, respectively.

Dependent variable: ΔSRISK	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)	(9)
Environmentally_Friendly_Index		-8.128*	-15.417***	-13.579***	-8.325**	-9.092**	-9.071**	-9.198**	-9.114**
		(4.053)	(4.820)	(4.872)	(3.577)	(4.095)	(4.073)	(4.047)	(4.023)
CCExposure	0.083*	0.099							
	(0.044)	(0.064)							
Wall Street Journal Climate Change News Index (log)			0.194						
			(0.234)						
Crimson Hexagon Negative Climate Change News Index (log)				0.183					
				(0.218)					
Media Climate Change Concerns Index					-0.021				
					(0.327)				
U.S. climate policy						0.239**			
						(0.092)			
International summits							0.318*		
							(0.172)		
Global warming								-0.303	
								(0.237)	
Natural disasters									0.079
									(0.175)
Constant	-1.822***	-2.619***	1.396	-2.076	-1.870***	-2.299***	-2.393***	-2.049**	-2.236**
	(0.527)	(0.937)	(1.275)	(1.296)	(0.684)	(0.795)	(0.850)	(0.857)	(0.862)
Control variables	Yes		Yes	Yes	Yes	Yes	Yes	Yes	Yes
Observations	5,676	3,778	2,191	2,889	4,335	3,466	3,466	3,466	3,466
Financial Institution FE	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes
Clusters	58	50	45	49	61	50	50	50	50
Adj. R^2	0.068	0.085	0.078	0.081	0.083	0.066	0.065	0.065	0.064

4.4.1. Robustness

In addition to the main analysis, we conduct several tests to check the reliability of our results. First, we examine our findings on climate-related physical risks. These risks are measured by the proportion of banks' exposure in each NWS region relative to the total exposure in the U.S. market. We investigate whether the results are driven more by regional exposure levels than by actual climate events. To address this, we add extra monthly lagged variables to our main regression model to show banks' exposure in each NWS region against the overall U.S. market exposure. The results in Table A. 4.1 in the appendix indicate that, regardless of the model used, the volume of loans a bank issues in a specific region does not explain differences in banks' systemic risk. Meanwhile, the findings regarding climate-based measures are consistent with what we found earlier.

Another test we conduct involves incorporating the lender's Environmental Score alongside the $Environmental\_Friendly\_Index$ to validate our main findings. These two indicators differ in that the Environmental Score evaluates a bank's overall practices and approach to environmental issues, while the $Environmental\_Friendly\_Index$ acts as a proxy for the bank's market share in sustainable loans, underscoring its commitment to eco-friendly lending. Furthermore, the Environmental Score may be affected by self-reported data. The results in Table A. 4.2 in the appendix show that our main results are still robust when considering the bank's Environmental Score.

Research often integrates Social and Governance factors with Environmental indicators to enhance understanding of a company's practices. We assess whether our analysis remains valid after adding these components to the index. We report the results in Table A. 4.3 in the appendix, which suggest that our main conclusions are unchanged. Nevertheless, to sharpen our focus on climate risks, we concentrate on the $Environmental\_Friendly\_Index$. This targeted approach allows us to explore climate-related issues without the influence of broader ESG factors.

Finally, we account for common time trends by including time fixed effects in the baseline specification. The results are reported in Table A. 4.4. The Environmentally Friendly Index remains statistically significant across all model specifications, confirming the persistent relationship between banks' environmental attitude and their systemic risk cross variations. The inclusion of time fixed effects reinforces our previous conclusions regarding Hypothesis 1. While in the baseline specifications temperature anomalies and extreme event costs were the most explanatory variables, the models with time fixed effects emphasize the role of the Southern PDSI-weighted drought index. Among the physical climate risk indicators, the temperature-weighted anomaly in the Southern region remains statistically significant across all specifications, indicating a robust relationship between rising temperatures in this economically important area and banks' systemic exposures. In contrast, the extreme event variables that were previously significant do not remain robust across all model specifications once time fixed effects are introduced. Overall, the results suggest that, after controlling for common time shocks, several climate variables of the Southern region continue to exhibit a significant association with cross-sectional variation in systemic risk.

The robustness analysis for the Western region provides partial support for Hypothesis 2. After controlling for time fixed effects, only the temperature weighted anomaly index becomes statistically significant across all specifications. This indicates that temperature deviations in the Western region retain independent explanatory power for banks' systemic exposures after accounting for common time trends. For the East, the inclusion of time fixed effects substantially alters the results. The Eastern precipitation weighted anomaly loses statistical significance, indicating that once common temporal patterns are controlled, precipitation shocks in the East no longer provide independent information for banks' systemic risk.

The results presented in Table A. 4.4 provide support for Hypothesis 3, particularly for the Central region. The coefficient associated with the Central PDSI weighted drought index remains statistically significant across all specifications, indicating a robust relationship between persistent drought conditions and banks' systemic risk exposures. The Central United States is largely characterized by a primary sector-oriented economy, where agriculture and related industries account for a substantial share of regional economic activity. Our main financial control variables, including market interconnectedness, banks' exposure to leveraged and covenant lite loan portfolios, and bank size in total assets, remain statistically significant and robust across all specifications, in line with prior literature (Cai et al., 2018; Sina et al., 2025), confirming that conventional determinants of systemic risk remain robust after controlling for climate and time effects.

Similarly, we include time fixed effects in the analysis that incorporates the literature-based variables. The results are reported in Table A.4.5 of the appendix. The variable measuring banks' environmentally friendly attitude remains robust across all model specifications, together with the variable capturing U.S. climate policy. These results are consistent with our hypothesis that the transition process generates additional uncertainty in financial markets and is associated with higher cross-sectional variation in banks' systemic risk.

4.5. Conclusions

Our analysis suggests that lending to environmentally conscious borrowers may help mitigate systemic risk, yet physical climate events and heightened attention to new policies can still raise market concerns. These findings suggest that banks remain significantly exposed to climate-related risks. Climate anomalies, particularly in the Southern and Eastern U.S., where syndicated lending is concentrated, are linked to higher systemic risk, while uncertainty surrounding climate policy appear to contribute to short-term instability. This indicates that, although banks are increasingly taking climate considerations into account, they may not yet have fully internalized the financial implications of physical and transition risks. To help strengthen resilience, banks could reassess capital buffers to reflect climate-related uncertainty and evaluate borrower resilience to policy shifts. At the same time, regulatory authorities could provide stable and actionable guidance to reduce uncertainty across political administrations. A feasible policy framework with a long-term horizon can facilitate the integration of climate risks, support a smoother transition, and help safeguard systemic stability. Overall, the main results support our hypotheses regarding the relationship between climate anomalies and extreme events affecting economic activity in regions where banks' exposure through syndicated lending is more pronounced (Hypotheses 1 and 2). In addition, for the Central region, the results point more strongly to the role of expectations surrounding a potential worsening of drought conditions (Hypothesis 3), rather than realized extreme events, as a key potential factor associated with systemic vulnerability.One limitation of this study is the absence of standardized metrics for assessing and disclosing climate-related variables (Billio et al., 2021), along with the lack of borrower-specific environmental data in the syndicated loan dataset. Greater transparency in firms' environmental commitments would support more accurate credit risk assessments, encourage targeted lending to sustainable borrowers, and improve alignment between credit flows and climate objectives. Moreover, access to a publicly available dataset on the allocation of government transition funds and their recipients would offer a complementary dimension to evaluate firms' exposure to public support during the transition.

Future research might consider extending this analysis to other markets, particularly the European syndicated loan market, where support for the energy transition is more institutionalized and policy-driven. Initiatives such as the EU Green Deal, the Sustainable Finance Disclosure Regulation (SFDR), and the EU Taxonomy provide a useful context to explore how regulatory frameworks, mandatory disclosures, and targeted public funding may shape banks' systemic risk exposures through climate-related lending behaviour. A comparative approach could offer insights into how government-led transition efforts affect the relationship between climate and systemic risk, especially when taking into account differences in national policies, such as those between Nordic and Mediterranean countries. To conclude, in our model, we consider multiple climate factors independently within the same framework. Building on this, future research could develop a model that incorporates scientific evidence showing that climate risks are often compounding. [28] Several studies demonstrate that these risks can interact and amplify each other (López et al., 2025; Dulin et al., 2025; Zscheischler et al., 2018), and accounting for such interactions could provide a deeper understanding of the extent to which climate hazards affect systemic risk.

[28] See for reference the website https://climate.sustainability-directory.com/term/compound-climate-risk/

APPENDIX TO CHAPTER 4

Table A. 4.1: Regional share

This table displays the results of panel regressions based on Equation (16), with the dependent variable being the ΔSRISK of U.S. lenders. Differently from the main analysis, we incorporate the regional share of syndicated loan issuance amounts for lenders. Other main independent variables are the one-month lagged climate-related risk variables, which serve as proxies for lenders' portfolio environmental risks and climate physical risk, as detailed in Section 4.2.1. Additional independent variables include lagged proxies of interconnectedness derived from syndicated loan networks, along with the syndication risk measure of leveraged and covenant-lite loans, as detailed in Section 4.2.2. The USRECD indicator, based on NBER data, identifies U.S. recession periods, taking a value of 1 during recessions and 0 otherwise, while its complement indicates non-recession periods. Other lagged control variables include the lender's total assets (in billions of dollars), market share in the U.S. syndicated loan market (as a percentage), the overall size of the syndicated loan market (in billions of dollars), and the lagged SRISK. All regressions are adjusted for fixed effects of the banks. The sample period covers monthly observations from 2004 to 2022. At the bottom of the table, information is provided on the number of observations, fixed effects, number of clusters (i.e., banks), and adjusted R-squared values. Significance levels are indicated by *, **, and ***, representing coefficients that are significantly different from zero at the 10%, 5%, and 1% levels, respectively.

Dependent variable: ΔSRISK	(1)	(2)	(3)	(4)	(5)	(6)
Environmentally_Friendly_Index	-8.299**	-8.237**	-7.124**	-7.376**	-7.243**	-7.113**
	(3.629)	(3.641)	(3.177)	(3.165)	(3.172)	(3.173)
Western syndicated loans share	-0.123	-0.927	-0.740	0.141	-0.579	-0.346
	(0.397)	(0.561)	(0.543)	(0.447)	(0.487)	(0.450)
Eastern syndicated loans share	0.265	0.033	0.061	0.327	0.066	0.053
	(0.209)	(0.263)	(0.267)	(0.240)	(0.284)	(0.277)
Central syndicated loans share	0.287	0.295	0.308	0.086	0.087	0.154
	(0.255)	(0.256)	(0.262)	(0.231)	(0.271)	(0.283)
Southern syndicated loans share	0.350	0.122	0.085	0.340	0.121	0.062
	(0.257)	(0.294)	(0.304)	(0.261)	(0.297)	(0.308)
Western PDSI−weighted anomaly index				0.139	0.247	0.291*
				(0.126)	(0.161)	(0.165)
Eastern PDSI−weighted anomaly index				-0.065	-0.058	-0.005
				(0.098)	(0.093)	(0.101)
Central PDSI−weighted anomaly index				0.177**	0.200**	0.155
				(0.084)	(0.084)	(0.094)
Southern PDSI−weighted anomaly index				-0.006	0.029	0.006
				(0.063)	(0.061)	(0.059)
Western temperature−weighted anomaly index		0.513*	0.483*		0.577**	0.562*
		(0.268)	(0.267)		(0.287)	(0.287)
Western precipitation−weighted anomaly index		0.549	0.379		0.270	0.089
		(0.408)	(0.420)		(0.390)	(0.392)
Eastern temperature−weighted anomaly index		0.081	0.067		0.092	0.078
		(0.067)	(0.067)		(0.067)	(0.067)
Eastern precipitation−weighted anomaly index		0.301*	0.347*		0.319*	0.355*
		(0.177)	(0.179)		(0.184)	(0.186)
Central temperature−weighted anomaly index		0.029	0.010		0.028	0.010
		(0.127)	(0.128)		(0.126)	(0.127)
Central precipitation−weighted anomaly index		-0.223	-0.289		-0.384	-0.383
		(0.407)	(0.429)		(0.396)	(0.414)
Southern temperature−weighted anomaly index		0.143**	0.156**		0.141**	0.153**
		(0.060)	(0.062)		(0.058)	(0.059)
Southern precipitation−weighted anomaly index		-0.403	-0.331		-0.381	-0.303
		(0.248)	(0.249)		(0.237)	(0.234)
Western extreme−weighted impact cost			0.693**			0.669**
			(0.317)			(0.332)
Eastern extreme−weighted impact cost			0.419			0.446
			(0.570)			(0.576)
Central extreme−weighted impact cost			-0.084			-0.250
			(0.488)			(0.528)
Southern extreme−weighted impact cost			1.848**			1.760**
			(0.790)			(0.779)
Control variables	Yes	Yes	Yes	Yes	Yes	Yes
Constant	-2.044***	-2.012***	-2.861***	-2.058***	-2.028***	-2.823***
	(0.682)	(0.688)	(0.898)	(0.679)	(0.684)	(0.904)
Observations	4,178	4,178	4,178	4,178	4,178	4,178
Financial Institution FE	Yes	Yes	Yes	Yes	Yes	Yes
Clusters	53	53	53	53	53	53
Adj. R^2	0.084	0.085	0.087	0.084	0.085	0.087

Table A. 4.2: The connection between systemic risk and climate risks, while accounting for the lender's environmental score

This table displays the results of panel regressions based on Equation (16), with the dependent variable being the ΔSRISK of U.S. lenders. Differently from the main analysis, we incorporate the lender environmental score. Other main independent variables are the one-month lagged climate-related risk variables, which serve as proxies for lenders' portfolio environmental risks and climate physical risk, as detailed in Section 4.2.1. Additional independent variables include lagged proxies of interconnectedness derived from syndicated loan networks, along with the syndication risk measure of leveraged and covenant-lite loans, as detailed in Section 4.2.2. The USRECD indicator, based on NBER data, identifies U.S. recession periods, taking a value of 1 during recessions and 0 otherwise, while its complement indicates non-recession periods. Other lagged control variables include the lender's total assets (in billions of dollars), market share in the U.S. syndicated loan market (as a percentage), the overall size of the syndicated loan market (in billions of dollars), and the lagged SRISK. All regressions are adjusted for fixed effects of the banks. The sample period covers monthly observations from 2004 to 2022. At the bottom of the table, information is provided on the number of observations, fixed effects, number of clusters (i.e., banks), and adjusted R-squared values. Significance levels are indicated by *, **, and ***, representing coefficients that are significantly different from zero at the 10%, 5%, and 1% levels, respectively.

Dependent variable: ΔSRISK	(1)	(2)	(3)
Environmentally_Friendly_Index	-8.081**	-8.105**	-7.979**
	(3.815)	(3.801)	(3.822)
Lender_environmental_score	0.011	0.012	0.011
	(0.010)	(0.010)	(0.010)
Western temperature−weighted anomaly index	0.346		0.350
	(0.239)		(0.233)
Western precipitation−weighted anomaly index	0.718		0.527
	(0.428)		(0.449)
Eastern temperature−weighted anomaly index	0.071		0.065
	(0.060)		(0.061)
Eastern precipitation−weighted anomaly index	0.359*		0.411*
	(0.202)		(0.212)
Central temperature−weighted anomaly index	0.075		0.055
	(0.140)		(0.141)
Central precipitation−weighted anomaly index	-0.364		-0.397
	(0.426)		(0.438)
Southern temperature−weighted anomaly index	0.162**		0.173**
	(0.067)		(0.066)
Southern precipitation−weighted anomaly index	-0.363		-0.337
	(0.346)		(0.345)
Western extreme−weighted impact cost		0.640	0.649
		(0.382)	(0.390)
Eastern extreme−weighted impact cost		0.272	0.298
		(0.620)	(0.628)
Central extreme−weighted impact cost		-0.183	-0.132
		(0.504)	(0.503)
Southern extreme−weighted impact cost		2.032**	2.000**
		(0.836)	(0.849)
Centrality × U.S. Recession	0.191**	0.179**	0.187**
	(0.084)	(0.087)	(0.087)
Centrality × U.S. Non-recession	-0.007	-0.003	0.003
	(0.040)	(0.041)	(0.040)
$SN\_RISK^{Lev\&CovLite}$ × U.S. Recession	0.711***	0.721***	0.717***
	(0.218)	(0.222)	(0.224)
$SN\_RISK^{Lev\&CovLite}$ × U.S. Non-Recession	-0.081	-0.087	-0.084
	(0.126)	(0.124)	(0.125)
Total Assets (B$)	0.002***	0.003***	0.003***
	(0.000)	(0.001)	(0.001)
Constant	-2.861***	-3.575***	-3.698***
	(0.952)	(1.138)	(1.132)
Control variables	Yes	Yes	Yes
Observations	3,604	3,604	3,604
Financial Institution FE	Yes	Yes	Yes
Clusters	45	45	45
Adj. R^2	0.085	0.086	0.087

Table A. 4.3: The connection between systemic risk and ESG borrowers factors within lenders' portfolios.

This table displays the results of panel regressions based on Equation (16), with the dependent variable being the ΔSRISK of U.S. lenders. Differently from the main analysis, we introduce the ESG_Friendly_Index as a proxy for lenders' portfolio environmental risks. Other main independent variables are the one-month lagged climate-related risk variables, which serve as proxies for climate physical risk, as detailed in Section 4.2.1. Additional independent variables include lagged proxies of interconnectedness derived from syndicated loan networks, along with the syndication risk measure of leveraged and covenant-lite loans, as detailed in Section 4.2.2. The USRECD indicator, based on NBER data, identifies U.S. recession periods, taking a value of 1 during recessions and 0 otherwise, while its complement indicates non-recession periods. Other lagged control variables include the lender's total assets (in billions of dollars), market share in the U.S. syndicated loan market (as a percentage), the overall size of the syndicated loan market (in billions of dollars), and the lagged SRISK. All regressions are adjusted for fixed effects of the banks. The sample period covers monthly observations from 2004 to 2022. At the bottom of the table, information is provided on the number of observations, fixed effects, number of clusters (i.e., banks), and adjusted R-squared values. Significance levels are indicated by *, **, and ***, representing coefficients that are significantly different from zero at the 10%, 5%, and 1% levels, respectively.

Dependent variable: ΔSRISK	(1)	(2)	(3)	(4)
ESG_Friendly_Index	-9.285**	-9.131*	-9.162**	-9.011*
	(4.578)	(4.583)	(4.571)	(4.580)
Western temperature−weighted anomaly index		0.319		0.326
		(0.212)		(0.209)
Western precipitation−weighted anomaly index		0.598		0.406
		(0.370)		(0.385)
Eastern temperature−weighted anomaly index		0.058		0.056
		(0.050)		(0.050)
Eastern precipitation−weighted anomaly index		0.318*		0.376**
		(0.167)		(0.174)
Central temperature−weighted anomaly index		0.071		0.047
		(0.113)		(0.113)
Central precipitation−weighted anomaly index		-0.263		-0.292
		(0.360)		(0.374)
Southern temperature−weighted anomaly index		0.151***		0.157***
		(0.050)		(0.050)
Southern precipitation−weighted anomaly index		-0.357		-0.310
		(0.247)		(0.247)
Western extreme−weighted impact cost			0.666**	0.676**
			(0.300)	(0.305)
Eastern extreme−weighted impact cost			0.379	0.383
			(0.522)	(0.529)
Central extreme−weighted impact cost			-0.156	-0.144
			(0.442)	(0.451)
Southern extreme−weighted impact cost			1.812**	1.794**
			(0.740)	(0.749)
Centrality × U.S. Recession	0.176**	0.183**	0.167**	0.174**
	(0.072)	(0.072)	(0.076)	(0.076)
Centrality × U.S. Non-recession	-0.004	0.001	0.003	0.008
	(0.034)	(0.033)	(0.034)	(0.033)
$SN\_RISK^{Lev\&CovLite}$ × U.S. Recession	0.722***	0.718***	0.734***	0.730***
	(0.196)	(0.196)	(0.202)	(0.203)
$SN\_RISK^{Lev\&CovLite}$ × U.S. Non-Recession	-0.093	-0.091	-0.096	-0.094
	(0.119)	(0.120)	(0.119)	(0.119)
Total Assets (B$)	0.003***	0.003***	0.003***	0.003***
	(0.000)	(0.000)	(0.000)	(0.000)
Constant	-1.864***	-2.001***	-2.645***	-2.788***
	(0.644)	(0.634)	(0.815)	(0.809)
Control variables	Yes	Yes	Yes	Yes
Observations	4,334	4,334	4,334	4,334
Financial Institution FE	Yes	Yes	Yes	Yes
Clusters	61	61	61	61
Adj. R^2	0.083	0.084	0.085	0.086

A.4 4: Relationship between systemic risk and climate risks - with time fixed effects.

This table displays the results of panel regressions based on Equation (16), with the dependent variable being the ΔSRISK of U.S. lenders. Differently from the main analysis, we include time fixed effects. The main independent variables are the one-month lagged climate-related risk variables, which serve as proxies for lenders' portfolio environmental risks and climate physical risk, as detailed in Section 3.2.1. Additional independent variables include lagged proxies of interconnectedness derived from syndicated loan networks, along with the syndication risk measure of leveraged and covenant-lite loans, as detailed in Section 3.2.2. The USRECD indicator, based on NBER data, identifies U.S. recession periods, taking a value of 1 during recessions and 0 otherwise, while its complement indicates non-recession periods. Other lagged control variables include the lender's total assets (in billions of dollars), market share in the U.S. syndicated loan market (as a percentage), the overall size of the syndicated loan market (in billions of dollars), and the lagged SRISK. All regressions are adjusted for fixed effects of the banks. The sample period covers monthly observations from 2004 to 2022. At the bottom of the table, information is provided on the number of observations, fixed effects, number of clusters (i.e., banks), and adjusted R-squared values. Significance levels are indicated by *, **, and ***, representing coefficients that are significantly different from zero at the 10%, 5%, and 1% levels, respectively.

Dependent variable: ΔSRISK	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)	(9)	(10)	(11)
Environmentally_Friendly_Index	-7.452*		-7.375*	-7.449*		-7.374*			-7.310*		-7.321*
	(3.778)		(3.779)	(3.788)		(3.788)			(3.805)		(3.814)
Western temperature−weighted anomaly index		0.393*	0.386*			0.378*	0.384*	0.503*	0.495*	0.498*	0.491*
		(0.216)	(0.217)			(0.219)	(0.218)	(0.257)	(0.259)	(0.261)	(0.263)
Western precipitation−weighted anomaly index		0.535	0.555			0.513	0.492	0.164	0.188	0.115	0.139
		(0.533)	(0.523)			(0.531)	(0.542)	(0.487)	(0.480)	(0.494)	(0.486)
Eastern temperature−weighted anomaly index		0.035	0.029			0.027	0.033	0.058	0.052	0.056	0.050
		(0.054)	(0.055)			(0.055)	(0.054)	(0.052)	(0.053)	(0.052)	(0.052)
Eastern precipitation−weighted anomaly index		0.211	0.209			0.207	0.209	0.214	0.214	0.213	0.213
		(0.175)	(0.174)			(0.175)	(0.175)	(0.185)	(0.185)	(0.186)	(0.186)
Central temperature−weighted anomaly index		0.024	0.023			0.025	0.026	-0.012	-0.013	-0.013	-0.014
		(0.108)	(0.108)			(0.104)	(0.105)	(0.099)	(0.098)	(0.095)	(0.094)
Central precipitation−weighted anomaly index		-0.060	-0.051			0.004	-0.006	-0.245	-0.238	-0.196	-0.188
		(0.390)	(0.400)			(0.422)	(0.412)	(0.391)	(0.402)	(0.397)	(0.408)
Southern temperature−weighted anomaly index		0.106*	0.104*			0.101*	0.103*	0.144**	0.141**	0.139**	0.136**
		(0.061)	(0.060)			(0.057)	(0.058)	(0.066)	(0.064)	(0.062)	(0.061)
Southern precipitation−weighted anomaly index		-0.067	-0.073			-0.073	-0.067	-0.172	-0.176	-0.168	-0.172
		(0.214)	(0.214)			(0.218)	(0.217)	(0.208)	(0.209)	(0.209)	(0.210)
Western PDSI−weighted								0.299	0.295	0.307	0.304
								(0.183)	(0.183)	(0.185)	(0.185)
Eastern PDSI−weighted								-0.049	-0.053	-0.047	-0.050
								(0.118)	(0.118)	(0.113)	(0.114)
Central PDSI−weighted								0.310**	0.305**	0.296**	0.291**
								(0.138)	(0.137)	(0.136)	(0.136)
Southern PDSI−weighted								0.206**	0.208**	0.222**	0.225**
								(0.094)	(0.093)	(0.104)	(0.103)

(Table A.4.4 - continues in the next page)

(Table A.4.4 - continued)

Dependent variable: ΔSRISK	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)	(9)	(10)	(11)
Western extreme−weighted impact cost				0.486	0.481	0.440	0.435			0.444	0.449
				(0.391)	(0.382)	(0.388)	(0.380)			(0.384)	(0.391)
Eastern extreme−weighted impact cost				-0.138	-0.134	-0.179	-0.176			-0.194	-0.197
				(0.682)	(0.665)	(0.681)	(0.663)			(0.661)	(0.678)
Central extreme−weighted impact cost				-0.350	-0.327	-0.346	-0.320			-0.466	-0.492
				(0.632)	(0.625)	(0.644)	(0.638)			(0.668)	(0.673)
Southern extreme−weighted impact cost				1.816*	1.860*	1.679*	1.722*			1.436	1.400
				(0.951)	(0.952)	(0.965)	(0.965)			(0.936)	(0.935)
Centrality × U.S. Recession	0.203**	0.209**	0.209**	0.205**	0.205**	0.211**	0.211**	0.204**	0.204**	0.206**	0.206**
	(0.092)	(0.093)	(0.092)	(0.092)	(0.092)	(0.092)	(0.093)	(0.094)	(0.093)	(0.094)	(0.093)
Centrality × U.S. Non-recession	-0.005	-0.001	-0.000	-0.005	-0.006	0.000	-0.001	-0.004	-0.003	-0.004	-0.003
	(0.026)	(0.026)	(0.026)	(0.025)	(0.025)	(0.025)	(0.025)	(0.026)	(0.026)	(0.025)	(0.025)
$\text{SN\_RISK}^{\text{Lev\&CovLite}}$ × U.S. Recession	0.755***	0.746***	0.751***	0.754***	0.749***	0.749***	0.745***	0.756***	0.761***	0.755***	0.760***
	(0.206)	(0.213)	(0.207)	(0.208)	(0.215)	(0.208)	(0.215)	(0.215)	(0.209)	(0.217)	(0.210)
$\text{SN\_RISK}^{\text{Lev\&CovLite}}$ × U.S. Non-Recession	-0.095	-0.098	-0.094	-0.094	-0.097	-0.093	-0.097	-0.092	-0.089	-0.091	-0.087
	(0.121)	(0.124)	(0.121)	(0.123)	(0.125)	(0.123)	(0.125)	(0.125)	(0.123)	(0.127)	(0.124)
Total Assets (B$)	0.002***	0.002***	0.002***	0.002***	0.002***	0.002***	0.002***	0.002***	0.002***	0.002***	0.002***
	(0.001)	(0.001)	(0.001)	(0.001)	(0.001)	(0.001)	(0.001)	(0.001)	(0.001)	(0.001)	(0.001)
Constant	-2.283***	-2.545***	-2.393***	-2.708***	-2.868***	-2.779***	-2.943***	-2.531***	-2.377***	-2.849***	-2.685***
	(0.773)	(0.734)	(0.770)	(0.880)	(0.857)	(0.887)	(0.866)	(0.781)	(0.815)	(0.888)	(0.911)
Control variables	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes
Observations	4,334	4,334	4,334	4,334	4,334	4,334	4,334	4,334	4,334	4,334	4,334
Financial Institution FE	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes
Time FE	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes
Clusters	61	61	61	61	61	61	61	61	61	61	61
Adj. R^2	0.101	0.100	0.101	0.101	0.100	0.102	0.100	0.101	0.102	0.101	0.103

A. 4.5: Examining the connection between systemic risk and climate change risk through variables identified in existing literature (Engle et al., 2020; Ardia et al., 2022; Faccini et al., 2023; Sautner et al., 2023) - with time fixed effects.

This table displays the results of panel regressions based on Equation (16), with the dependent variable being the ΔSRISK of U.S. lenders. Differently from the main analysis, we include time fixed effects. The primary independent variables are the climate change risk variables developed by Engle et al. (2020), Ardia et al. (2022), Sautner et al. (2023), and Faccini et al. (2023), as outlined in Section 3.5.3. Additional variables include one-month lagged climate-related risk factors, which act as proxies for lenders' portfolio environmental risks and climate physical risks, as described in Section 3.2.1. Moreover, the model incorporates lagged proxies of interconnectedness derived from syndicated loan networks, along with a syndication risk measure for leveraged and covenant-lite loans, detailed in Section 3.2.2. The USRECD indicator, based on NBER data, identifies U.S. recession periods, taking a value of 1 during recessions and 0 otherwise, while its complement indicates non-recession periods. Other lagged control variables include the lender's total assets (in billions of dollars), market share in the U.S. syndicated loan market (as a percentage), the overall size of the syndicated loan market (in billions of dollars), and the lagged SRISK. All regressions are adjusted for the fixed effects of the banks. The sample period spans monthly observations from 2004 to 2022. At the bottom of the table, details are provided regarding the number of observations, fixed effects, number of clusters (i.e., banks), and adjusted R-squared values. Significance levels are indicated by *, **, and ***, denoting coefficients that are significantly different from zero at the 10%, 5%, and 1% levels, respectively.

Dependent variable: ΔSRISK	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)	(9)
Environmentally_Friendly_Index		-10.986**	-13.550***	-15.354***	-10.559**	-8.387**	-8.394**	-9.188**	-8.449**
		(4.763)	(4.870)	(4.815)	(4.280)	(3.854)	(3.831)	(4.045)	(3.805)
CCExposure	-0.021	0.036							
	(0.063)	(0.067)							
Wall Street Journal Climate Change News Index (log)			0.329						
			(0.251)						
Crimson Hexagon Negative Climate Change News Index (log)				0.200					
				(0.197)					
Media Climate Change Concerns Index					-0.053				
					(0.200)				
U.S. climate policy						0.214**			
						(0.093)			
International summits							0.209		
							(0.194)		
Global warming								-0.312	
								(0.244)	
Natural disasters									-0.192
									(0.214)
Constant	-3.498***	-2.973***	-1.461	1.371	-2.003**	-1.801**	-1.927**	-2.063**	-1.718**
	(0.919)	(1.016)	(1.468)	(1.273)	(0.806)	(0.708)	(0.748)	(0.872)	(0.783)
Control variables	Yes		Yes	Yes	Yes	Yes	Yes	Yes	Yes
Observations	5,676	3,778	2,191	2,889	4,335	3,466	3,466	3,466	3,466
Financial Institution FE	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes
Time FE	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes
Clusters	58	50	45	49	61	50	50	50	50
Adj. R^2	0.070	0.073	0.079	0.083	0.097	0.084	0.083	0.083	0.083

5. Broken Pledges: How Politics Undermines Net-Zero Ambitions in Banking

5.1. Introduction

This study is motivated by the following event: in the wake of the recent U.S. presidential election results, several major North American banks, including Citigroup, Bank of America, Morgan Stanley, Wells Fargo, and Goldman Sachs, announced their withdrawal from the NZBA. At first glance, this decision is not surprising, given the new administration's scepticism about climate change, the decision to leave the Paris Agreement, the relaxation of environmental regulations, and support for fossil fuel projects. Within the broader U.S. political context, these withdrawals can be understood as reflecting a combination of incentives and constraints. On one hand, profitable opportunities in carbon-intensive sectors likely acted as a motivating factor. More significantly, however, these decisions often seem to reflect direct political pressure, concerns over potential legal disputes, and expectations from shareholders and investors on financial performance. In several Republican-led states, authorities have warned that participation in such alliances could be interpreted as breaching antitrust regulations or could trigger exclusion from state-level contracts. Such warnings not only raise the risk of costly legal battles but also the possibility of reputational damage, especially in regions where climate commitments are politically contested.

For instance, the state of Texas[29] illustrates the stakes involved, being a dominant energy producer that accounts for 43% of the nation's crude oil output and 27% of gross natural gas

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[29] In Texas, the Attorney General linked NZBA membership to possible violations of anti-boycott laws, prompting threats of exclusion from government contracts (S&P Global, 2025, link; Texas Attorney General, 2025). A coalition of 22 Republican state attorneys general also sent letters to climate-aligned financial alliances, warning of potential antitrust violations and market distortions, and launched investigations into large banks such as Citigroup, Bank of America, Morgan Stanley, and JPMorgan.

withdrawals.[30] These developments take place in a political environment where ESG-related commitments are often portrayed as constraining market freedom or advancing particular values. Under this framing, climate alliances such as the NZBA are not viewed as neutral instruments for managing risk, but as politicized obligations that may limit competition, steer corporate strategies, or grant advantages to certain sectors.

In light of these recent events, this study considers an important question: how do political developments relate to banks' strategic decisions regarding NZBA membership? The answer is important considering that also Japanese banks, only a few months after their U.S. counterparts, also decided to withdraw from the NZBA. This suggests that political pressure from the United States may exert a significant influence on large Japanese banks. These banks appear to balance the goals of preserving profitability, securing supply chains, and meeting investor expectations, while also continuing to support domestic green initiatives. A plausible explanation lies in the substantial financial and operational links between Japanese banks and American institutions. By the end of 2020, nearly half of their 4.85 trillion U.S. dollars in overseas loans and investments was concentrated in the United States. [31] This strong interconnection, combined with Japan's reliance on stable access to foreign resources, is further reflected in the record 605.8 trillion yen in total outstanding lending reached in 2024. This growth was partly driven by rising raw material prices and the depreciation of the yen.[32]

A key question that could naturally arise and we first attempt to answer in this study, is whether participation in this Alliance has offered banks measurable benefits in reducing climate-related risk. To explore this, we first investigate whether banks that have met preliminary targets under the NZBA framework have achieved tangible reductions in their climate risk exposure. The analysis addresses these issues by examining the relationship between banks' involvement in the NZBA and their progress toward climate risk exposure goals. To our knowledge, this study represents the first effort to answer this question. This is likely because the NZBA, established only in 2021, is the first banking alliance to provide the data necessary for this type

[30] See for reference statistics on https://www.eia.gov/state/rankings/?sid=GA#/series/46
[31] See, for reference, the article published by S&P Global, "Japan banks face volatility, default risks offshore in hunt for higher returns," April 14, 2021.
[32] See, for reference, the article published by The Japan Times, "Japan bank lending hits record high at end of 2024, " January 11, 2025

of analysis at the banking level. Using the forward-looking CRISK metric (Jung et al., 2025), which quantifies banks' vulnerability to climate-induced financial risks, we examine variation within NZBA member banks. Among these members, we find that banks that achieve early-stage NZBA targets demonstrate a tangible reduction in their exposure to climate risk.

The second question concerns the factors that may drive banks to withdraw from the NZBA. Financial institutions, and banks in particular, play a central role in shaping capital allocation, managing environmental risk, and influencing corporate behaviour through their lending and investment decisions. Our findings indicate that, among NZBA member banks, long-term net-zero commitments tend to be stronger under supportive political and regulatory conditions. Conversely, variation in withdrawal decisions appears to correspond with political developments, with some banks showing higher likelihood of withdrawal under challenging political conditions. The Net-Zero Banking Alliance provides empirical evidence of this fragile equilibrium. As one of the most ambitious and structurally rigorous initiatives for banks, the NZBA, launched by the United Nations Environment Programme Finance Initiative (UNEP FI), commits member banks to achieving net-zero greenhouse gas emissions across their lending and investment portfolios by 2050. Distinct from other voluntary frameworks, the NZBA requires banks to establish concrete interim targets, transparently disclose emissions and progress, and align their strategies with the internationally agreed goal of limiting global warming to 1.5°C. This framework is designed to foster institutional accountability and accelerate the financial sector's contribution to the global energy transition. Member banks are expected not only to report emissions data but also to demonstrate substantive progress in decarbonizing portfolios, particularly in high-emitting sectors such as fossil fuels, transportation, and energy-intensive manufacturing. This approach seeks to ensure that net-zero commitments are reflected in measurable actions rather than in forward-looking self-reported statements.

Overall, our results show that variation in CRISK is not strongly associated with membership alone. Rather, it is the achievement of interim decarbonization targets, the concrete milestones set within the NZBA framework, that correlates with a measurable decline in the banks' CRISK metric. While banks advance toward short-term targets at differing rates, the shared long-term objective of achieving net-zero emissions by 2050 remains universally recognised. This reflects broad acknowledgment of both the existential threat posed by climate change and the financial risks associated with inaction. Despite observable effects on banks' risk reduction, the only variable consistently significant across models explaining the probability of withdrawal from the NZBA is the election of a climate-sceptical president. The implications are considerable. Voluntary frameworks can support decarbonization when politics are favourable, but they lack the resilience to maintain progress through changing political cycles. These developments highlight an opportunity for regulators and the banking sector to develop medium- to long-term strategies aimed at achieving net-zero targets with reduced dependence on shifting political conditions.

The rest of the paper is structured as follows: Section 5.2 reviews the related literature, Section 5.3 outlines the methodology employed, Section 5.4 presents the data, Section 5.5 discusses the main results and the robustness checks. Finally, Section 5.6 concludes this study.

5.2. Related literature

By quantitatively analysing the relationship between NZBA participation, shaped by political election outcomes, and banks' climate risk, this study aims to address a gap in the existing literature. Much of the academic studies on climate finance focus on the Paris Agreement's broader influence or on firms' climate-related disclosures. Fewer studies explore how financial institutions themselves, particularly banks, adjust their risk profiles in response to structured climate commitments. For instance, Degryse et al. (2023) find that green banks adjust loan pricing in favour of environmentally friendly firms following the Paris Agreement. While Reghezza et al. (2022) demonstrate that European banks reallocate credit away from polluting firms. Yet the specific mechanisms through which climate alliances affect institutional risk remain underexplored. Recent scholarship highlights the growing role of central banks in promoting financial stability in the face of climate risks. Wang et al. (2025), for example, examine how climate change exacerbates financial vulnerabilities and assess the mitigating effects of central banks' green policy frameworks. Using panel data from 115 countries between 1984 and 2021, they find that extreme weather events, especially floods and wildfires, significantly elevate financial risk, with effects persisting for multiple years. Regulatory instruments and green finance policies can partially offset these effects, although the extent of mitigation is influenced by national credit market characteristics. While not solely responsible for solving environmental issues, central banks, especially in developing economies, can play a targeted role in promoting green finance where optimal policies are lacking (Dikau & Volz, 2018).

In parallel, a growing body of research has explored how climate-related policies and agreements influence financial markets, particularly corporate behaviour. Due to the widespread availability of firm-level climate disclosures, this research has often focused on non-financial corporations. In contrast, the banking sector has historically lacked consistent and transparent reporting on climate alignment, making difficult empirical evaluations across banks. The establishment of the NZBA in 2021 marked a significant step forward by requiring member banks to adopt credible net-zero targets and disclose interim goals, thereby enhancing institutional accountability and enabling more rigorous data-driven assessments.

To date, some studies have examined the implications of joining the NZBA for banks themselves. In particular, Maio et al. (2023) focus on Global Systemically Important Banks (G-SIBs) and find that membership in the alliance has begun to yield some progress, especially in terms of increased ambition and transparency regarding climate-related targets. However, several critical issues remain unaddressed. These include the wide variation in targets across sectors, often underpinned by unclear or poorly articulated methodologies; a continued reliance on carbon offsets rather than actual reductions in financed emissions; limited portfolio coverage that omits substantial exposures; and exclusion policies that lack clarity, thereby undermining the transparency and credibility of banks' transition strategies. Focusing on Global Systemically Important Banks (G-SIBs), Beltran et al. (2023) observe advancements in the reduction of direct emissions. However, only a limited number of institutions have begun to assess financed emissions[33], despite these accounting for the majority of banks' overall climate footprint. On the portfolio side, many G-SIBs have publicly committed to scaling up sustainable finance, yet their ongoing exposure to fossil fuel-related activities remains substantial and misaligned with net-

[33] One could argue that such decisions are not accidental but rather reflect a deliberate strategic choice by the bank. As Sir Chris Hohn, founder of TCI, states: "Any bank making a Net Zero promise whilst actively lobbying against necessary climate regulation – such as mandatory disclosure of borrowers' emissions and climate action plans – is greenwashing. Shareholders should vote against the directors of banks who are hiding their exposure to climate risk." (source: https://influencemap.org/report/Finance-and-Climate-Change-17639)

zero targets. The study also highlights that several banks have initiated efforts to identify climate risk drivers and to develop tools for assessing their potential impact on business models and risk profiles, although such practices are still in early development. Overall, while there is evidence of progress in being aware of climate objectives, the pace and scope of these efforts vary considerably across regions and dimensions of bank strategies. Adopting a similar perspective, the report by InfluenceMap (2022) provides an in-depth analysis of the disconnect between the long-term climate commitments and the limited short-term actions of the world's 30 largest listed financial institutions. While nearly all have pledged to reach net-zero emissions by 2050, many continue to provide substantial financing to fossil fuel sectors and maintain affiliations with industry associations that oppose sustainable finance regulations. Only a small number of institutions demonstrate genuine leadership, whereas the majority lack concrete short-term plans, sector-specific targets, and alignment with the 1.5°C climate trajectory.

Despite the limitations of the alliance, Liu et al. (2024) find that NZBA member banks disclose significantly higher-quality environmental information compared to non-member banks. Their comparative analysis of five NZBA banks and four Chinese non-member banks over the period 2016–2021 shows a clear improvement in the quality and clarity of disclosures among alliance members. Adopting a different angle, Romero and González (2025) investigate how NZBA membership affects banks' loan portfolio strategies. They find that green lending rises after joining the alliance, but this increase is mainly concentrated in advanced economies and comes at the expense of green lending to emerging markets. Moreover, NZBA banks become more selective in their lending practices, reducing the number of deals and focusing increasingly on clients based in developed countries. More recently, following the exit of major global banks in the United States from the Net-Zero Banking Alliance (NZBA), Yildirim and Vanwalleghem (2026) employ an event-study approach to examine financial market reactions to both the formation and subsequent weakening of the alliance. Their results show that only founding members experienced significant stock price declines, suggesting that investors perceived these initial commitments as credible and economically costly. By contrast, later entrants to the alliance, as well as subsequent withdrawals by member banks, generated little to no market reaction. This pattern indicates that the credibility of the NZBA eroded over time, as its governance weakened under political pressure and participant attrition. Our study closely relates to this evidence by extending the literature with a systematic analysis of both the benefits and the institutional fragilities associated with NZBA participation.

Multiple studies have assessed the transformative influence of the Paris Agreement, adopted in 2015 and enforced from 2016, on both corporate behaviour and financial institutions. Its central aim is to limit global temperature rise to well below 2°C, with signatories committing to nationally determined contributions (NDCs). Reghezza et al. (2022), for instance, document a reallocation of European bank lending away from polluting firms toward greener borrowers, particularly among banks that are more capitalized or engaged in climate initiatives. Similarly, Aslan et al. (2022) analyze the Turkish banking sector, showing that banks reduce credit exposure in more polluted provinces following the Agreement's adoption, especially in regions with elevated climate risk. Bruno and Lombini (2023) further explore the effects of climate transition risks on bank lending behaviour, finding that banks impose higher loan margins on polluting borrowers in countries with stronger climate awareness. However, they observe limited reductions in overall credit supply, highlighting the complex and non-linear dynamics between climate risk and credit allocation. Tolliver et al. (2019) investigate the rise of green bonds, noting a surge in issuances used to finance renewable energy, transportation, and water infrastructure projects aligned with both the Paris Agreement and the UN Sustainable Development Goals (SDGs). Their findings underscore the pivotal role of commercial banks and multilateral institutions in deploying green capital to facilitate decarbonization. Beyond credit and investment, climate risk also affects firm-level financial policy. Chang et al. (2024) examine the influence of climate risk on corporate payout strategies across 45 countries, finding that firms in high-risk environments reduce dividends and prefer share repurchases, which offer greater flexibility amid climate-induced volatility. The shift became more pronounced after the Paris Agreement, particularly in countries with cultural traits favoring uncertainty avoidance and long-term planning.

Climate-related disclosures have also become a focal point of governance and investor scrutiny. The Task Force on Climate-related Financial Disclosures (TCFD), established by the Financial Stability Board in 2015, has become a global benchmark for climate transparency. Empirical studies indicate a steady increase in TCFD-aligned reporting since 2017. Ding et al. (2023) develop a novel metric using textual analysis of annual reports from 2010 to 2018, finding that high-emission firms in carbon-intensive sectors voluntarily disclose more climate information, particularly in TCFD-recommended areas such as governance, risk management, and strategy. Disclosure patterns vary by jurisdiction: UK firms emphasize governance and strategy, while US firms' reporting is more strongly influenced by emissions levels. Xhindole et al. (2025) examine climate-related disclosures by listed firms in Italy and Spain over the period 2020–2023, two countries characterised by comparable institutional and financial structures. Their analysis reveals widespread adoption of the Task Force on Climate-related Financial Disclosures (TCFD) framework, yet limited integration of climate risks into firms' broader risk management systems. The findings suggest that national regulatory contexts influence disclosure emphasis, with Italian firms prioritizing governance-related aspects and Spanish firms placing greater focus on both narrative and quantitatively disclosure of risk management information. In Asia, Gao et al. (2024) examine the impact of TCFD-aligned disclosures on green innovation in Chinese A-share companies. While disclosure generally supports innovation, excessive emphasis on governance is negatively associated with innovation, reflecting how institutional context can mediate the effectiveness of transparency efforts. Banks have increasingly endorsed the TCFD framework, though their motivations and disclosure quality vary. Lee et al. (2024) assess voluntary climate disclosures by the world's 100 largest banks, finding that those operating in common law countries with stronger investor protections and better environmental performance are more likely to adopt TCFD practices. Board independence and diversity positively affect disclosure quality, while board size and Chief Executive Officer (CEO) power do not. Interestingly, in jurisdictions with high shareholder litigation risk, board independence may actually reduce disclosure levels, highlighting the nuanced and sometimes counterintuitive governance dynamics surrounding climate transparency.

Another significant initiative is the Principles for Responsible Banking (PRB), introduced in 2019 by the UNEP Finance Initiative to align banking activities with the Sustainable Development Goals (SDGs) and the Paris Agreement. Feridun and Talay (2023), examining data from 46 European countries, find that a higher proportion of wholesale banks adhering to the PRB is associated with greater progress toward achieving the SDGs, particularly in sectors such as renewable energy and sustainable agriculture. In contrast, retail banks appear to have a more constrained capacity to support these objectives, contributing less directly to

SDG-related outcomes. Taken together, these studies emphasize the growing influence of climate-related initiatives on financial decision-making, credit allocation, disclosure practices, and institutional risk management. However, while the effects of broad frameworks like the Paris Agreement and TCFD have been widely studied, the specific implications of voluntary alliances such as the NZBA on banks' climate risk profiles remain insufficiently explored. This study contributes to filling this gap by offering empirical evidence on whether NZBA participation, particularly banks' self-reported first target progress on decarbonization targets, correlates with reductions in climate-related financial risk. In doing so, it also considers the political and institutional factors that may condition the durability and credibility of such voluntary commitments.

This study examines how political election results in the U.S. shape banks' approaches to managing climate risk, contributing to the growing but still limited literature that links political risk with climate-related banking strategies. Research on political risk in firms is expanding (e.g., Gad et al., 2024; Hasan et al., 2022; Huang et al., 2023; Wang et al., 2024). Detomasi (2007) shows that firms' adoption of CSR initiatives is shaped by domestic political structures. By similar considerations, it is plausible to think that climate-related initiatives by financial institutions are similarly influenced by the political frameworks of their home countries. Empirical evidence in banking, however, remains limited. This is partly because political risk, though conceptually straightforward, is difficult to measure in a way suitable for banking-sector analysis. As a result, there is little empirical evidence or shared theoretical guidance on how political dynamics influence banks' climate-related decisions. We address this gap by providing evidence on the role of political factors in banks' participation in voluntary climate initiatives, such as the Net-Zero Banking Alliance. Within climate finance, Basha et al. (2025) find that political risk at the firm level tends to heighten corporate climate risk, particularly when political actors focus on companies with high emissions or those facing environmental lawsuits. Firms with strong managerial expertise are better positioned to counteract these negative impacts. Focusing on U.S. presidential elections as a source of global political uncertainty, Gong et al. (2022) show that these events affect international stock markets, whereas elections in firms' home countries have no comparable impact. Firms with high climate risk experience sharper return volatility and stronger return co-movements during such periods, illustrating how political uncertainty can intensify vulnerabilities for climate-exposed firms. This is understandable given the stark contrasts in climate change policies and approaches adopted by successive U.S. presidents, with those aligned with the political left generally prioritizing environmental regulations and climate mitigation measures, and those aligned with the political right typically favoring less regulatory intervention and placing greater emphasis on economic and energy market considerations.

Investigating the banking sector, Shabir et al. (2024) show that political and climate risks weaken financial stability and reduce the effectiveness of diversification, with stronger impacts on conventional banks and those in GCC countries than on Islamic banks and those in non-GCC regions. This finding highlights the importance of regulatory context and banking models in shaping resilience. Similarly, Hainz and Kleimeier (2011) find that political risk significantly shapes loan contract design, increasing the use of project finance and encouraging development bank involvement in syndicated loans, with its influence in some cases exceeding that of legal and institutional quality. Liu and Ngo (2014) analyze the timing of bank failures around U.S. elections and identify a statistically significant reduction in failure incidence in the pre-election period, particularly in states where governors possess stronger legislative influence. Their results are consistent with strategic regulatory behavior aimed at limiting politically costly disruptions to financial stability. In a related setting, Leverty and Grace (2018) study the U.S. insurance industry and provide evidence that regulatory actions deviate from fundamentals around elections. They document election-cycle delays in regulatory takeovers, which are most pronounced when electoral competition is intense, suggesting that political and career incentives systematically affect supervisory decisions. Looking at the corporate sector, Stef et al. (2022) exploit panel variation across 82 countries over the period 2005–2017 to assess the role of electoral cycles in shaping insolvency outcomes. Their estimates indicate that the time required to resolve corporate distress increases around legislative elections, particularly in the year preceding the vote and for reorganization procedures. This pattern is consistent with firms and creditors postponing restructuring decisions in response to heightened political uncertainty and anticipated policy changes. By contrast, the analysis detects no statistically significant effects associated with presidential election cycles.

Still focusing on the banking sector, Koetter and Popov (2021) provide evidence from the European context, particularly Germany. Their findings indicate that political dynamics influence banks' lending behavior toward regional governments. Using data from 1992 to 2018, they show that state-level party turnover is associated with a significant increase in lending by local savings banks to their home-state government. This increase is accompanied by a corresponding decline in private lending. No comparable effect is observed for cooperative banks with similar regional structures. These results suggest that political frictions can shape the lending strategies of government-owned banks and affect their local development objectives. Cunha and Kern (2022) fill an important gap in the literature, and analyse the cross-border effects of political shocks in the banking sector. They examine the role of global banks as key providers of credit and liquidity and show that political shocks generate international spillovers through cross-border bank flows. Exploiting the unexpected outcomes of the 2016 U.S. presidential election and the Brexit referendum as quasi-exogenous shocks, the authors identify significant financial spillovers affecting a broad set of countries.

Methodology

5.2.1. Climate risk variables

We use the CRISK measure of financial institutions' climate risk from NYU's V-Lab as the primary variable to assess banks' monthly climate risk, following the definition provided by Jung et al. (2025). The $CRISK$ measures the expected capital shortfall of a financial firm during a climate crisis, specifically when the value of the firm's stranded assets portfolio declines by more than 50% within a six-month period. The climate risk ($CRISK$) measure is defined as:

$$CRISK = k * Debt - (1 - k) * (1 - LRMES) * MV, \tag{17}$$

where: k is the prudential capital requirement (8% for firms in Africa, Asia, and the Americas; 5.5% for firms in Europe), $LRMES$ represents the expected fractional loss of equity when the stranded assets portfolio[34] experiences the crisis threshold (default set at 50%), MV is the market value of the firm.

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[34] As explained in detail by Jung et al. (2025), stranded assets are evaluated using a "stranded asset factor" that reflects the risk of fossil fuel reserves becoming economically unviable due to climate policies, with research indicating that significant portions of oil, gas, and coal reserves must remain untapped to keep global warming below 2 degrees Celsius. The stranded asset portfolio, developed by Litterman (2023) and the World Wildlife Fund, includes a 70% long position in the VanEck Vectors Coal ETF (KOL), a 30% long position in the Energy Select Sector SPDR ETF (XLE), and a short position in the SPDR S&P 500 ETF Trust (SPY); after KOL's closure, it uses the average returns of the top five coal companies. This portfolio serves as a proxy for market expectations about future climate risks. To assess stranded asset risks, a scenario is created where the factor declines by 50% over six months, representing a severe stress test aligned with the 1% quantile of past returns. Such scenarios help banks evaluate their exposure to potential market value losses during the transition to a low-carbon economy, highlighting the necessity for effective measurement and management of stranded asset risks.

5.2.2. Model

Our empirical analysis employs two distinct models. The first model evaluates whether membership in the NZBA, specifically through the achievement of initial decarbonization targets, impacts changes in the bank's climate risk. The second model examines the determinants of banks' decisions to exit the NZBA Alliance, considering institutional, political and economic factors.

5.2.2.1. Climate Risk and the NZBA Alliance

To examine the potential connection between climate risk and NZBA membership, we introduce the following econometric model:

$$
\begin{aligned}
&\Delta CRISK_{i,t} = \alpha + \beta_1(Joining\ NZBA_{i,t}) \\
&+\beta_2(Distance\ from\ NZBA's\ first\ target_{i,t}) \\
&+\beta_3(NZBA\ first\ target\ completion_{i,t}) \\
&+\beta_4(Climate - sceptic\ President\ _t) \\
&+\beta_5(Global\ financial\ crisis_t) \\
&+\beta_6(Paris\ Agreement_t) \\
&+\beta_7(Covid\ pandemic_t) \\
&+\beta_8(Total\ assets_{i,t-1}) \\
&+\beta_9(Leverage_{i,t-1}) \\
&+\beta_{10}(ROA_{i,t-1}) \\
&+\beta_{11}(Loan\ loss\ reserves\ relative\ to\ gross\ customer\ loans\ \&\ advances_{i,t-1}) \\
&+\beta_{12}(Non - interest\ income\ relative\ to\ Operating\ revenues_{i,t-1}) \\
&+\beta_{13}(LaggedCRISK_{i,t}) \\
&+Fixed\ Effects_i + Fixed\ Effects_t + \varepsilon_{i,t}
\end{aligned}
\tag{18}
$$

Where $\Delta CRISK_{i,t}$ represents the change in climate risk for institution i at time t, with the observation being the last daily data point in the reference month as indicated by V-lab; $LaggedCRISK_{i,t}$ is the lagged value of climate risk for institution i at time t, included to account for persistent effects; $Joining\ NZBA_{i,t}$ is a dummy variable that equals 1 if institution i has joined the National Banking Association (NZBA) at time t; $Distance\ from\ NZBA's\ first\ target_{i,t}$ represents the monthly distance to the first target set by bank i at time t, aimed at progressively aligning with the NZBA's final target; and $NZBA\ first\ target\ completion_{i,t}$ indicates whether institution i has completed the first NZBA target at time t. The $Climate - sceptic\ President_t$ denotes the election, at time t, of a U.S. president characterised by a sceptical stance toward climate change policies. Additional dummy variables represent the $Global\ financial\ crisis_t$, $Paris\ Agreement_t$, and $Covid\ pandemic_t$, each equal to 1 during their respective event. The accounting-based variables include: $Total\ assets_{i,t}$[35], which represents the total assets on the balance sheet of institution i at time t; the ratio of loan loss reserves to gross customer loans and advances for institution i at time t is defined by $Loan\ loss\ reserves\ relative\ to\ gross\ customer\ loans\ \&\ advances_{i,t}$,; $Leverage_{i,t}$ measures the leverage level of institution i at time t; $ROA_{i,t}$ is the return on assets (ROA) for institution i at time t; $Non - interest\ income\ relative\ to\ operating\ revenues_{i,t}$ is the ratio of non-interest income to operating revenues for institution i at time t. Finally, we include fixed effects specific to institution i and time t; and $\varepsilon_{i,t}$ is the error term for institution i at time t.

We propose alternative versions of this model to investigate how the exclusion or inclusion of additional variables influences the robustness of the coefficients. To address the non-stationarity of CRISK, we define our dependent variable in first differences[36].

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[35] We employ quarterly data whenever available and project them to the following months until the next available data point. In cases where quarterly accounting information is not available, we rely on semi-annual or annual data instead.

[36] However, the results remain consistent in both interpretation and statistical significance when the variable is expressed in millions of US dollars.

5.2.2.2. Analysis of political and financial factors influencing withdrawal from the NZBA alliance

To examine the factors that affect a bank's decision to withdraw from the NZBA (Net Zero Banking Alliance), we employ the following logit model:

$$\begin{aligned}
&Logit(P)_{i,t} = \alpha + \beta_1\left(CRISK_{i,t}\right) \\
&+\beta_2\left(NZBA\ first\ target\ completion_{i,t}\right) \\
&+\beta_3(Climate - sceptic\ President_t) \\
&+\beta_4\left(Total\ Assets_{i,t-1}\right) \\
&+\beta_5(Leverage_{i,t-1}) \\
&+\beta_6(ROA_{i,t-1}) \\
&+\beta_7(Loan\ loss\ reserves\ relative\ to\ gross\ customers\ loans\ \&\ advances_{i,t-1}) \\
&+\beta_8(Non - interest\ income\ relative\ to\ operating\ revenues_{i,t-1}) \\
&+\varepsilon_{i,t}
\end{aligned} \tag{19}$$

In this model, the dependent variable is a binary outcome that indicates whether a bank has withdrawn from the alliance (1) or not (0). The remaining variables correspond to those employed in the previously specified model.

5.3. Data

Our empirical analysis utilizes a comprehensive set of data sources, which are categorized into institutional data related to the NZBA, climate indicators, a political factor, macroeconomic data reflecting the impact of global shocks such as the 2008 financial crisis and the COVID-19 pandemic, and bank-specific financial information. Table 5.1 details these sources, outlining the variables employed in the study alongside concise descriptions of each. Table 5.2 presents the correlation matrix for the key variables, providing preliminary insights consistent with the patterns observed in the empirical results. Notably, there is a negative correlation between the achievement of initial NZBA targets and a bank's exposure to climate risk (-0.030), suggesting that progress in sustainability commitments generally corresponds with reduced climate-related vulnerabilities. Conversely, the political variable, measuring the election of a climate-sceptical president, exhibits a positive correlation with climate risk (0.011), suggesting that market participants interpret political developments as significant signals concerning a bank's environmental strategy and risk exposure. Regarding bank-specific financial indicators, the data indicate that climate risk shows relatively low sensitivity to traditional balance sheet variables. However, there is a positive correlation between bank size and NZBA membership (0.065), implying that larger institutions are more inclined to participate in international climate initiatives.

5.3.1. Climate and political data

Among the key climate-related variables incorporated in our empirical analysis is the Climate Risk Index (CRISK[37]), as defined by Jung et al. (2025) and obtained from the Volatility Laboratory at the NYU Stern Volatility and Risk Institute (https://vlab.stern.nyu.edu). Figure 5.1 presents the monthly average of the bank-level Climate Risk Index (Average CRISK), measured in millions of U.S. dollars, spanning the period from June 2000 to July 2025. The data reveal a sustained increase in climate-related risks over this timeframe. To contextualize this trend, we highlight the political landscape by shading in gray the periods corresponding to U.S. Republican presidential administrations. For clarity, Table 5.3 provides an overview of these administrations, including their climate policies, instances of rolling back predecessor initiatives, and withdrawals from international agreements, all of which significantly influenced the trajectory of climate risk. For each time period, we also indicate whether the House of Representatives and the Senate are controlled by the same party as the President. This is because, as studies show, a polarised Congress creates political stalemate and lowers the probability of presidential proposals becoming law (Repetto and Andrés, 2023). This effect is likely even more

[37] Jung et al. (2025) provide an extensive explanation of how CRISK departs from SRISK, the bank-level systemic risk measure developed by Brownlees and Engle (2017). CRISK is tailored to assess how resilient financial institutions are to climate-related threats. Although it builds on the methodological foundation of SRISK, it introduces specific modifications aimed at capturing a wider spectrum of climate risk drivers and developing stress-test scenarios targeted to these factors.

pronounced in the case of climate change policies, where views diverge between parties (Park et al., 2014; Guber et al., 2021).

Figure 5.1 indicates an initial peak in climate risk in December 2008, primarily attributable to the global financial crisis. This surge reflects heightened uncertainty and volatility within financial markets during this period. The lead-up to this peak coincides with the presidency of George W. Bush, whose administration implemented several notable actions impacting climate risk. Notably, the United States' withdrawal from the Kyoto Protocol in 2001 marked a reduction in international climate commitments. Additionally, the launch of the Climate Change Science Program (CCSP) in 2002 sought to coordinate climate research across federal agencies to enhance understanding of global climate change and its potential consequences. The Energy Policy Act of 2005 further shaped the landscape by providing subsidies favoring fossil fuels while offering limited support for renewable energy. Collectively, these policies did not facilitate a course of action aimed at mitigating climate change over the years.

During Barack Obama's presidency (2009–2016), climate risk exhibited notable variation but remained relatively stable in the final years of the mandate (2013–2016), within an approximate range of –10 to +10 billion. This period of stabilization appears to be the result of several significant climate initiatives, including the American Recovery and Reinvestment Act (2009), which allocated substantial funding for renewable energy projects; the implementation of stringent national fuel economy standards (2009); the signing of the Paris Agreement (2015); and the introduction of the Clean Power Plan (2015). Collectively, these measures likely helped moderate the trajectory of climate risk, with their effects extending into the subsequent administration until around mid-2019.

During President Donald Trump's first term (2017–2020), climate risk reached a marked peak, probably partly reflecting market uncertainty associated with the COVID-19 pandemic. The administration's policy decisions—including the 2017 announcement of withdrawal from the Paris Agreement, the expansion of oil and gas drilling beginning in 2017, approval of the Keystone XL pipeline in 2019, the formal initiation of the Paris Agreement withdrawal process in 2019 (completed in 2020), and the rollback of the Clean Power Plan in 2019—contributed to an environment of heightened climate vulnerability. Collectively, these measures intensified climate-related risks throughout this period. In contrast, the period following President Joe Biden's inauguration is marked by a gradual decline in climate risk, attributable to a broad set of climate policy initiatives. Notable measures include rejoining the Paris Agreement in 2021, re-establishing the National Climate Task Force, committing the federal government to net-zero emissions by 2050, issuing executive orders on climate change and environmental justice, and enacting the Inflation Reduction Act in 2022, which allocated $370 billion to climate-related investments. The final section of the chart reflects the return of President Donald Trump's administration, characterised by renewed climate scepticism and the announcement of several major policy reversals, most notably the immediate withdrawal from the Paris Agreement.

5.3.2. Net Zero Banking Alliance

For our empirical analysis, we use panel data for 85 institutions, selected based on the availability of all relevant variables. This analysis focuses specifically on banks participating in the NZBA. Table 5.4 presents a detailed overview of regional participation in the NZBA from 2021 to 2026. European banks consistently represent the highest share of participants, reaching a peak of 38% in 2021 and maintaining a significant presence with 11% in 2022. This pattern highlights the strong and sustained commitment of European banks to net-zero objectives. Cumulatively, banks from the Asia-Pacific and North American regions followed, contributing 16% and 13% to total participation, respectively. Banks typically set initial NZBA targets within one to two years of joining, indicating strong short-term engagement. However, recent years have witnessed a noticeable wave of withdrawals. In North America, 12% of the banks exited the alliance between December 2024 and January 2025, while the Asia-Pacific region experienced a 5% reduction in March 2025. These withdrawals have been widely linked to the political shift following the 2024 U.S. presidential election. For instance, The Guardian (8 January 2025) reported that "Six big US banks quit net zero alliance before Trump inauguration," suggesting expectations over impending regulatory rollbacks. Similarly, the Financial Times (7 April 2025) raised questions about the alliance's future in its article, "Can the Net-Zero Banking Alliance retain its sole Japanese member?"

Table 5.1: Variables sources and descriptions

This table outlines the key variables used in this analysis, along with the sources from which they were obtained or defined.

Variable name	Source	Description
CRISK	The Volatility Laboratory of the NYU Stern Volatility and Risk Institute (https://vlab.stern.nyu.edu)	CRISK is the expected capital shortfall of a financial firm in a climate crisis where the stranded assets portfolio falls by more than 50% in a six-month period (Jung et al., 2025).
Joining NZBA	Variable defined according to the information available on the Net-Zero Banking Alliance website (https://www.unepfi.org/net-zero-banking/ website)	Dummy variable equal to 1 from the month and year the bank joins the Net-Zero Banking Alliance.
Distance from NZBA first target	Variable defined according to the information available on the Net-Zero Banking Alliance website (https://www.unepfi.org/net-zero-banking/ website)	The number of months remaining to achieve the NZBA's first target, as defined by the bank.
NZBA first target completion	Variable defined according to the information available on the Net-Zero Banking Alliance website (https://www.unepfi.org/net-zero-banking/ website)	Dummy variable equal to 1 starting from the month in which the first NZBA target is achieved.
Climate - sceptic President	The https://www.whitehousehistory.org/the-presidents-timeline	Dummy variable equal to 1 when a climate change-skeptical president is elected.
Bank's financed emissions	Tables based on the report "Banking on Climate Chaos – Fossil Fuel Finance Report 2025," available at: https://it.scribd.com/document/639060301/All-League-Tables-Banking-on-Climate-Chaos-2023	The measure, gathered from the 2025 BOCC report, tracks the total value of loans, underwriting, bonds, and acquisition financing channeled by the top global banks to fossil fuel companies.

(Table 5.1 - continues in the next page)

(Table 5.1 - continued)

Total Assets (B$)	Orbis	Banks' total assets on the balance sheet, which represent the overall size of the bank.
Leverage	Orbis	Banks' leverage on the balance sheet, which represents the ratio of total assets to equity.
ROA	Orbis	Non-interest income relative to operating revenues, which represents the proportion of a bank's revenues generated from sources other than interest, such as fees and commissions.
Non-interest income relative to operating revenues	Orbis	Proportion of a company's total operating revenues that comes from non-interest income sources.
Loan loss reserves relative to gross customer loans & advances	Orbis	Proportion of a bank's reserves set aside for potential loan losses relative to its total gross customer loans and advances.
G-SIBs	The https://www.fsb.org/	Dummy variable equal to 1 if the financial institution is classified as a Globally Systemically Important Bank (G-SIB). Data are updated annually based on the latest FSB list. For periods not covered, the most recent available G-SIB composition is assumed.
Global financial crisis	The NBER (https://www.nber.org/research/data/us-business-cycle-expansions-and-contractions)	Dummy variable that equals 1 during the U.S. recession triggered by the Global Financial Crisis, specifically from January 2008 to June
Paris agreement	Self-defined	Dummy variable that equals 1 from January 2016, considering that the Paris Agreement was signed in December 2015.
Covid pandemic	The https://www.who.int/europe/emergencies/situations/covid-19	Dummy variable equal to 1 during the COVID-19 peak period (March 2020 to mid-2021), aligned with declining cases and increased vaccination efforts.

Table 5.2: Correlation matrix

This table presents the correlation matrix for the key variables employed in this study, including ΔCRISK, Joining NZBA, Distance from NZBA first target, NZBA first target completion, Withdrawal from NZBA, U.S. presidential election results, Total assets, Leverage, ROA, Loan loss reserves relative to gross customer loans and advances, Non-interest income relative to operating revenues, Global financial crisis, Paris Agreement, the COVID-19 pandemic, and banks' financed emissions. For the latter variable, data are available only for a smaller sample of banks and are presented in the robustness analysis.

	ΔCRISK	Joining NZBA	Distance from NZBA first target	NZBA first target completion	Withdraw from NZBA	USA presidential election results	Total assets	Leverage	ROA	Loan loss ratio (*1)	Non - interest ratio (*2)	Global financial crisis	Paris Agreement	Covid pandemic	Banks' financed emissions
ΔCRISK	1														
Joining NZBA	-0.019*	1													
Distance from NZBA first target	0.027*	-0.124*	1												
NZBA first target completion	-0.030*	0.634*	-0.747*	1*											
Withdraw from NZBA	-0.008*	-0.059*	-0.474*	0.371*	1										
USA presidential election results	0.011*	-0.167*	-0.158*	0.019*	0.246*	1									
Total assets	0.000	0.065*	-0.078*	0.083*	0.032*	-0.023*	1								
Leverage	-0.001	-0.021*	0.027*	-0.026*	0.002	-0.028*	-0.214*	1							
ROA	0.003	0.040*	0.001	0.028*	0.016*	-0.059*	-0.246*	0.171*	1						
Loan loss ratio (1)	-0.001	-0.065*	0.057*	-0.070*	-0.037*	0.056*	-0.184*	0.234*	0.001	1					
Non - interest ratio (2)	0.005	0.000	-0.023*	0.011	0.001	-0.010	0.278*	-0.189*	-0.126*	-0.205*	1				
Global financial crisis	0.046*	-0.115*	0.035*	-0.091*	-0.036*	-0.143*	0.012	0.008	0.040*	-0.059*	-0.002	1			
Paris Agreement	-0.008	0.463*	-0.140*	0.363*	0.143*	0.574*	-0.012	-0.029*	-0.015*	0.059*	-0.022*	-0.249*	1		
Covid pandemic	-0.015*	-0.071*	0.075*	-0.088*	-0.035*	0.271*	0.002	-0.008	-0.067*	0.031*	-0.005	-0.068*	0.273*	1	
Banks' financed emissions	0.006	-0.099*	0.092*	-0.116*	0.041*	0.096*	0.558*	0.098*	-0.016	-0.076*	0.382*	-	-	0.044*	1

** indicates significance at least at the 5% level*

(1) Loan loss reserves relative to gross customers loans & advances

(2) Non - interest income relative to Operating revenues

Figure 5.1: Average Climate Risk Index (CRISK) across U.S. presidential administrations from 2000 to 2025

This graph shows the monthly average bank-level Climate Risk Index (CRISK) from June 2000 to July 2025, measured in millions of U.S. dollars (left axis). The gray shaded areas indicate periods of Republican presidential administrations in the U.S., while the unshaded areas represent Democratic presidential administrations.

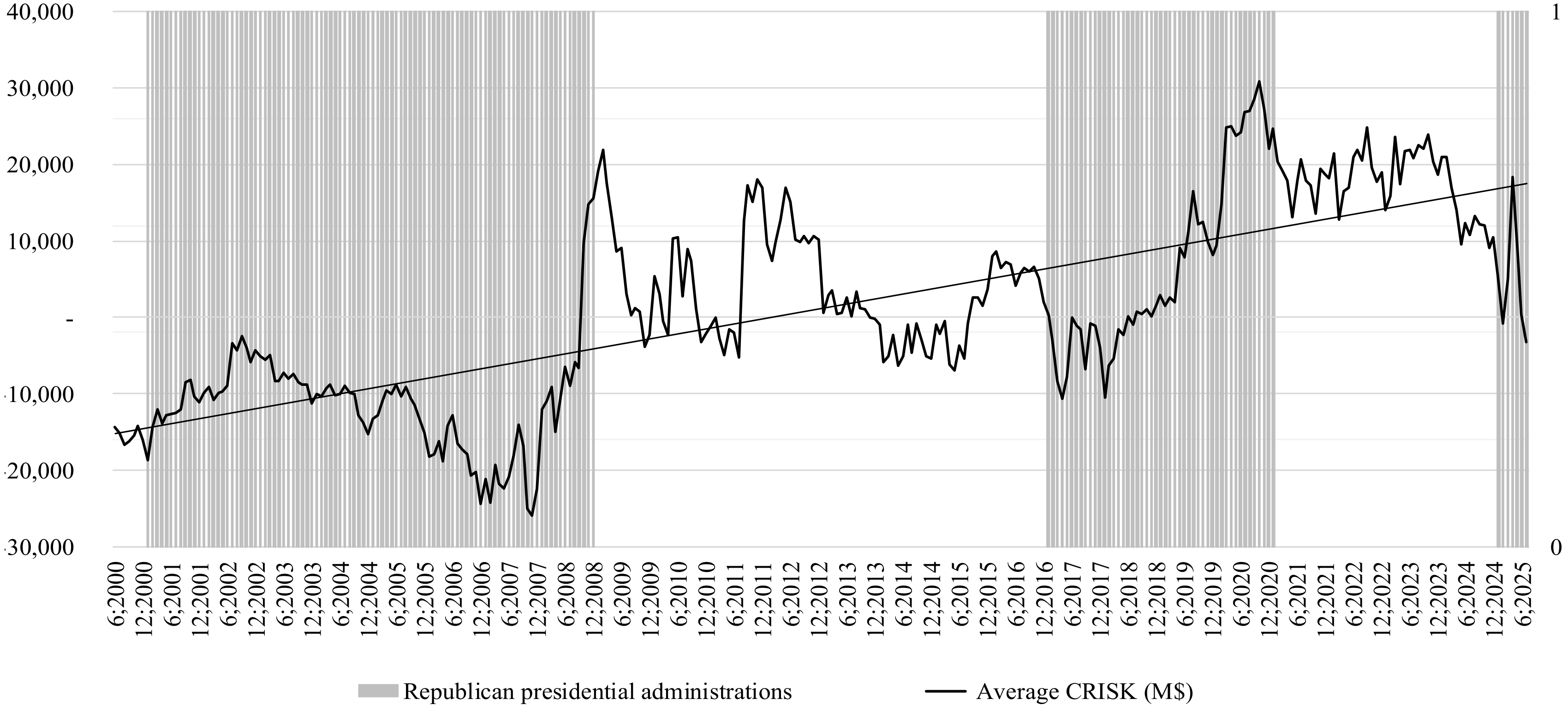

Table 5.3: USA presidential election and actions on climate change

This table summarizes U.S. presidential elections from 2000 to 2025, highlighting the distinction between Republican and Democratic administrations. It also indicates which party held control of the House of Representatives and the Senate during each presidency. Additionally, it outlines key climate change initiatives for each year, providing a comprehensive overview of environmental actions during this period.

Year	President	Rep./Dem. President	Rep./Dem. House of Representatives	Rep./Dem. Senate	Actions on climate change
2000	Bill Clinton	Dem	Rep	Rep	Signed the Kyoto Protocol (not ratified) and supported environmental protection initiatives (1993–2001).
2001	George W. Bush	Rep	Rep	Rep	Withdrew from the Kyoto Protocol (2001).
2002	George W. Bush	Rep	Rep	Rep	Introduced the Climate Change Science Program (2002): The CCSP was a federal initiative designed to coordinate and integrate climate research across multiple U.S. government agencies. Its primary goal was to improve the understanding of global climate change, including its causes, impacts, and potential responses.
2003	George W. Bush	Rep	Rep	Rep	
2004	George W. Bush	Rep	Rep	Rep	
2005	George W. Bush	Rep	Rep	Rep	Passed the Energy Policy Act (2005): provided subsidies for fossil fuels and some support for renewable energy.
2006	George W. Bush	Rep	Dem	Rep	
2007	George W. Bush	Rep	Dem	Dem	
2008	George W. Bush	Rep	Dem	Dem	
2009	Barack Obama	Dem	Dem	Dem	Stimulus funding for renewable energy through the American Recovery and Reinvestment Act (ARRA) of 2009 included major clean energy investments. In May 2009, President Obama announced the first national greenhouse gas emissions and fuel economy standards for cars and light trucks. These regulations aimed to raise average fuel efficiency to 35.5 miles per gallon (mpg) by 2016. This represented a historic agreement between automakers, the federal government, and California, which maintained its own stricter standards.
2010	Barack Obama	Dem	Dem	Dem	
2011	Barack Obama	Dem	Rep	Dem	
2012	Barack Obama	Dem	Rep	Dem	In August 2012, President Obama finalized a second round of standards covering model years 2017–2025. The target was an average fuel efficiency of 54.5 miles per gallon by 2025 (measured under laboratory conditions; real-world values are expected to be lower). These regulations also aimed to reduce greenhouse gas emissions from vehicles by approximately 50% compared to 2010 levels.
2013	Barack Obama	Dem	Rep	Dem	
2014	Barack Obama	Dem	Rep	Dem	
2015	Barack Obama	Dem	Rep	Rep	Signing of the Paris Agreement (2015). Introduction of the Clean Power Plan (2015), aiming to reduce carbon emissions from power plants by 32% by 2030 compared to 2005 levels.
2016	Barack Obama	Dem	Rep	Rep	

(Table 5.3 - continues in the next page)

(Table 5.3 – continued)

2017	Donald Trump	Rep	Rep	Rep	The announcement of withdrawal from the Paris Agreement occurred in 2017. During President Donald Trump's administration, primarily between 2017 and 2020, there was a notable expansion of oil and gas drilling, alongside the approval of the Keystone XL pipeline.
2018	Donald Trump	Rep	Rep	Rep	
2019	Donald Trump	Rep	Dem	Rep	The formal withdrawal process from the Paris Agreement began in 2019. The Clean Power Plan was officially rolled back by the President Donald Trump's administration in June 2019.
2020	Donald Trump	Rep	Dem	Rep	Completion of the withdrawal process from the Paris Agreement (2020).
2021	Joe Biden	Dem	Dem	Dem	Rejoining the Paris Agreement (2021). Several executive orders aimed at tackling climate change were issued, including measures to address environmental justice, re-establish the National Climate Task Force, and direct the federal government to achieve net-zero emissions by 2050.
2022	Joe Biden	Dem	Rep	Dem	Enacted the Inflation Reduction Act (2022), allocating $370 billion for climate-related investments.
2023	Joe Biden	Dem	Rep	Dem	
2024	Joe Biden	Dem	Rep	Dem	
2025	Donald Trump	Rep	Rep	Rep	On January 20, 2025, President Trump signed the Executive Order 14162 to immediately withdraw the U.S. from the Paris Agreement. Rolled back Environmental Protection Agency (EPA) regulations and canceled $3.7 billion in clean energy project grants. Declared a national energy emergency to accelerate fossil fuel infrastructure development.

Table 5.4: Annual Shares of signature, first target, and withdrawal for NZBA members

This table provides an overview of participation levels among the final sample of banks analyzed within the context of the Net-Zero Banking Alliance (NZBA) from 2021 to 2026. The sample includes a total of 85 banks. It shows annual participation rates, calculated by dividing the number of banks in each region and category (including signatories, initial targets, and withdrawals) by the total number of banks in the sample. The table is organized by regions as defined by the NZBA: Europe, Asia-Pacific, North America, and Others, which includes Africa & the Middle East and Latin America & the Caribbean.

Year	Region	Signature share	First target share	Withdrawal share
2021	Europe	38%	-	-
	Asia Pacific	9%	-	-
	North America	13%	-	-
	Other	8%	-	-
2022	Europe	11%	26%	-
	Asia Pacific	5%	4%	-
	North America	-	5%	-
	Other	1%	4%	-
2023	Europe	8%	18%	-
	Asia Pacific	1%	7%	-
	North America	-	8%	-
	Other	2%	5%	-
2024	Europe	2%	7%	-
	Asia Pacific	1%	4%	-
	North America	-	-	5%
	Other	-	1%	-
2025	Europe	-	8%	-
	Asia Pacific	-	1%	5%
	North America	-	-	7%
	Other	-	2%	-
2026	Europe	-	-	-
	Asia Pacific	-	1%	-
	North America	-	-	-
	Other	-	-	-

5.4. Results

Our primary regression model examines variation in climate risk (ΔCRISK) among NZBA member banks and its association with institutional, political, financial, and economic variables. Table 5.5 reports the results of panel regressions examining the determinants of monthly changes in banks' climate risk (ΔCRISK), using data from June 2000 to July 2025 for 85 banks. The analysis consists of six model specifications that progressively integrate institutional (NZBA-related) and political dimensions, while controlling for financial and economic factors. Across model specifications [1] to [6], the coefficient for the $Joining\ NZBA$ dummy variable is statistically not significant, suggesting that within-NZBA variation in climate risk does not systematically differ according to the timing of joining. The positive and statistically significant coefficient for the distance from the NZBA's first target indicates that as the monthly distance from the target increases, so does the climate risk associated with the bank's first achievement towards its larger goal of net-zero emissions by 2050. The coefficient for the dummy variable indicating the completion of the NZBA's first target is negative and statistically significant in specification [3], suggesting a reduction in climate risk. However, this effect is not robust across specifications.

The $Climate - sceptic\ President$ dummy is highly significant and positive across any model specification. This indicates that when a climate-sceptical president is elected in the U.S., banks' cross-sectional climate risk increases, likely reflecting expectations of regulatory rollbacks and reduced climate policy support. Financial control variables reveal that higher leverage is associated with increased climate risk, possibly because more highly leveraged banks may have less financial flexibility to manage or adapt to climate-related exposures. Conversely, greater profitability (as measured by ROA) is linked to lower climate risk, likely reflecting that well-performing banks have more resources and stronger risk management practices. Other financial indicators do not exhibit consistent effects on climate risk, implying that their influence is either indirect or limited and highly sensitive to the inclusion of additional control variables.

Global events demonstrate differentiated impacts on banks' climate risk. The variable capturing the global financial crisis is associated with a pronounced increase in climate risk, likely reflecting heightened systemic vulnerabilities. In contrast, the $COVID\ pandemic$ variable corresponds to a significant decrease in risk, potentially due to lower emissions and reduced economic activity. The $Paris\ Agreement$ variable shows a strong negative effect in specifications including political controls (models [5] and [6]), suggesting that global policy commitments can contribute to climate risk mitigation. This may also signal heightened market sensitivity to climate policies during periods of political transition, particularly under climate-sceptical leadership. The $Lagged\ CRISK$ variable is strongly negative and significant in all specifications, suggesting a degree of mean reversion in climate risk over time. Overall, these results, alongside the robustness tests detailed in 5.5.1, show that within-NZBA variation in climate risk is consistently associated with the election of a climate-sceptical president. This finding highlights how political leadership may influence climate-related risk exposure among NZBA members.

Table 5.6 presents the results of the logit regression (Equation 19), where the dependent variable captures a bank's decision to withdraw from the Net-Zero Banking Alliance. We report the marginal effects to facilitate the interpretation, showing the change in the probability of withdrawal associated with a one-unit change in each explanatory variable. The analysis incorporates political, climate-related, and financial variables to identify the main drivers of this decision. In specification [1], the coefficient on CRISK is negative and statistically significant, suggesting that banks with higher exposure to climate risk are less likely to exit the NZBA. However, this result is not robust, as it loses significance once political variables are included. The positive and significant coefficient for the post-target dummy after achieving the first NZBA targets suggests a higher likelihood of withdrawal. Nonetheless, this result may also reflect the overlap between the post-target period and the election of a sceptical president. The $Climate - sceptic\ President$ variable consistently shows a positive and significant effect in specifications [2], [3], and [5], indicating that banks are more likely to withdraw when a president sceptical of climate change is elected. This is consistent with how recent events have been commonly interpreted in the news. Other financial controls, when considered alongside the robustness tests, do not exhibit consistent or significant effects, indicating a limited role in explaining withdrawal behaviour.

Overall, our results indicate that within the NZBA, climate risk and withdrawal probability vary systematically with the election of a climate-sceptical president. This finding underscores the relevance of political factors relative to financial controls in shaping climate-related behaviour among alliance members. Given that the NZBA was established only in 2021, these developments represent an opportunity to reinforce the Alliance by explicitly incorporating political uncertainty and other factors that may affect banks' actual progress toward decarbonization targets into the refinement of membership criteria.

5.4.1. Robustness

To assess the robustness of our findings, we employed a series of regression models incorporating various fixed effects. Table A. 5.1 in the appendix reports the results for various model specifications: specifications [1] and [2] include regional fixed effects; specifications [3] and [4] incorporate country fixed effects; specifications [5] and [6] introduce interactions between bank-specific and country fixed effects; and specifications [7] and [8] include interactions between bank-specific and regional fixed effects. Across all these models, the main findings concerning the relationship between banks' climate risk exposure and the key explanatory variables explained in the main results remain consistent, thereby confirming them.

We incorporate the bank environmental pillar score into our analysis to examine its influence on our primary findings. This inclusion allows us to assess whether a bank's environmental performance impacts its exposure to climate-related risks. However, due to limited availability of environmental scores across the entire sample and time frame, our dataset is consequently reduced. As presented in Table A. 5.2, our analysis does not reveal a statistically significant relationship between the environmental pillar score and climate risk. This outcome, while seemingly counterintuitive, suggests that a bank's climate risk profile may already embed environmental considerations. Therefore, the environmental pillar score does not exhibit an additional, distinct effect in our model. Looking at the probability of withdrawal from the Alliance, Table A. 5.3 shows no statistically significant relationship with the environmental scores. However, the previous conclusion regarding the political factor remains valid. This finding suggests that the decision to withdraw is not primarily driven by a bank's environmental performance, but rather by broader political factors.

To assess more directly the role of banks' financed emissions, we include as an additional explanatory variable the one-year lagged value of financed emissions. A potential concern is that variation in financed emissions may not be strongly associated with membership timing, but rather reflects differences among NZBA banks' historical and structural exposures. Figure A. 5.1 presents the time series of banks' financed emissions, expressed in billions of U.S. dollars, for the three largest U.S. banks in terms of both financed emissions and systemic relevance (JPMorgan, Citigroup, and Bank of America), alongside the sample average. The markers denote the year in which each of the three banks first achieved a decarbonization target under the NZBA framework. The data show that, within the NZBA sample, financed emissions for the three largest U.S. banks and the sample average reached historical lows in the years following 2021, highlighting patterns of variation among members over time. However, consistent with recent developments and withdrawals from the NZBA, the values now appear to be on an upward trajectory. A major limitation of this analysis is the relatively limited availability of financed emissions data, not only for the period prior to the Paris Agreement but also for medium- and smaller-sized banks included in the sample. Consequently, the robustness of these within-NZBA patterns should be reassessed in the future as more comprehensive data become available. The results, presented in Table A.5.4 of the appendix, indicate that the coefficient on this variable is not statistically significant. This outcome suggests that, within NZBA members, the absolute level of financed emissions is not closely associated with short-term variation in the climate risk indicator.A plausible explanation is that financed emissions are relatively stable over time and primarily reflect banks' long-term structural exposures. In contrast, the climate risk indicator is designed to capture monthly fluctuations in market perceptions and climate-related financial vulnerabilities. By contrast, in the logit specification reported in Table A.5.5, the coefficient on financed emissions is statistically significant, with a positive marginal effect. This finding implies that banks with higher levels of financed emissions exhibit a greater probability of withdrawing from the NZBA. While financed emissions do not closely track monthly climate risk, they are associated with differences in banks' likelihood of withdrawing from the NZBA, reflecting how structural exposure may shape strategic choices within the Alliance. Institutions with substantial exposure to carbon-intensive financing face stronger tensions between their business models and the commitments associated with NZBA membership, which increases the likelihood of exit. This pattern is observable among several large global banks, including JPMorgan, Citigroup, and Bank of America, which exhibit both high emissions financing and recent withdrawal decisions within the NZBA sample[38].

To conclude our analysis, we narrow the focus to Globally Systemically Important Banks (G-SIBs) that are members of the NZBA. This focused approach significantly reduces the sample size, rendering it primarily an exercise in examining the behaviour of the political variable within this context. Consequently, the findings should be interpreted with caution, as a longer time frame is necessary to derive robust conclusions. Given their size and regulatory exposure, these institutions are expected to be particularly sensitive to shifts in political leadership and policy direction. Notably, most of the banks that have withdrawn from the NZBA are classified as systemically important. This observation implies that the pressures arising from political changes may disproportionately impact these major players, thereby influencing their commitment to sustainability initiatives. We present the results in Tables A.5.6 and A.5.7, which show, respectively, the outcomes of a panel regression and a panel logit model. In Table A. 5.6, we observe that the main findings from our broader sample are robust within this subgroup. The coefficient associated with the election of a climate-sceptical president is larger for globally systemically important banks (G-SIBs), with a value of around 9.460. This substantial magnitude indicates that variation in climate risk and strategic responses among these major institutions is closely associated with political developments. The logit model results in Table A. 5.7, also reinforce the robustness of our main conclusions within the G-SIB sample.

[38] See for reference https://oilchange.org/wp-content/uploads/2024/07/BOCC_2024_vF1.pdf

Table 5.5: Determinants of climate risk — institutional, political, economic, and financial factors

This table presents the estimation results from the panel regression specified in Equation (18), where ΔCRISK is the dependent variable, measuring the monthly change in the climate risk indicator developed by Jung et al. (2025). The explanatory variables include institutional factors related to NZBA membership: a dummy variable for Joining NZBA (equal to 1 starting from the month the bank joins), Distance from NZBA's first target (indicating the number of months to the initial target), and a dummy for NZBA first target completion (equal to 1 from the month the bank meets its initial goals). The variable Climate - sceptic President is a dummy equal to 1 when a president sceptical of climate change is elected. Additional dummy variables represent the Global Financial Crisis, Paris Agreement, and COVID-19 pandemic, each equal to 1 during their respective event periods. Financial control variables include Total assets, Leverage, Return on Assets (ROA), Loan loss reserves relative to gross customer loans, and Non-interest income relative to operating revenues. The model also includes Lagged CRISK to capture persistence in climate risk. All regressions include fixed effects for financial institutions and use monthly data from June 2000 to July 2025. At the bottom of the table, we report the number of observations, bank and year fixed effects, the number of clusters (financial institutions), and adjusted R-squared values. Robust standard errors are clustered at the bank level. Asterisks denote statistical significance: * at the 10% level, ** at the 5% level, and *** at the 1% level.

Dependent variable: ΔCRISK	(1)	(2)	(3)	(4)	(5)	(6)
Joining NZBA	0.071			-0.178		-0.056
	(0.374)			(0.419)		(0.422)
Distance from NZBA's first target		0.034**		0.030*		0.033*
		(0.015)		(0.018)		(0.018)
NZBA first target completion			-0.803**	-0.330		-0.291
			(0.312)	(0.356)		(0.355)
Climate - sceptic President					4.646***	4.762***
					(0.759)	(0.805)
Global financial crisis	2.822***	2.823***	2.820***	2.821***	2.822***	2.822***
	(0.913)	(0.912)	(0.912)	(0.913)	(0.912)	(0.913)
Paris Agreement	-0.457	0.286	0.315	0.566	-5.077***	-4.210***
	(0.873)	(0.613)	(0.671)	(0.781)	(1.228)	(1.223)
Covid pandemic	-2.384***	-2.308***	-2.401***	-2.359***	-2.842***	-2.777***
	(0.464)	(0.455)	(0.470)	(0.461)	(0.513)	(0.497)
Total assets	1.031	1.042	1.043	1.047	1.035	1.051
	(0.798)	(0.796)	(0.793)	(0.795)	(0.797)	(0.796)
Leverage	0.127**	0.119**	0.118**	0.115**	0.126**	0.116**
	(0.057)	(0.055)	(0.055)	(0.056)	(0.056)	(0.056)
ROA	-0.244**	-0.251**	-0.253**	-0.256**	-0.238*	-0.248**
	(0.122)	(0.125)	(0.125)	(0.124)	(0.123)	(0.123)
Loan loss reserves relative to gross customers loans & advances	0.027	0.031	0.030	0.031	0.026	0.031
	(0.027)	(0.027)	(0.027)	(0.027)	(0.027)	(0.027)
Non - interest income relative to Operating revenues	0.001	0.002	0.001	0.001	0.001	0.002
	(0.008)	(0.008)	(0.008)	(0.008)	(0.008)	(0.008)
Lagged CRISK	-0.093***	-0.093***	-0.093***	-0.093***	-0.093***	-0.093***
	(0.019)	(0.019)	(0.019)	(0.019)	(0.019)	(0.019)
Constant	-2.910***	-2.881***	-2.865***	-2.857***	-2.920***	-2.877***
	(0.712)	(0.716)	(0.718)	(0.716)	(0.714)	(0.716)
Observations	19,869	19,869	19,869	19,869	19,869	19,869
Year FE	Yes	Yes	Yes	Yes	Yes	Yes
Bank FE	Yes	Yes	Yes	Yes	Yes	Yes
Adj R-squared	0.0536	0.0538	0.0537	0.0537	0.0543	0.0543
Number of banks	85	85	85	85	85	85

Table 5.6: Factors influencing withdrawal from the Net Zero Banking Alliance (NZBA)

This table presents the estimation results from the logit regression specified in Equation (19), where the dependent variable is the decision to withdraw from the Net-Zero Banking Alliance (NZBA). The explanatory variables include the bank's CRISK measure, a dummy for NZBA first target completion (equal to 1 from the month the bank meets its initial goals), and a dummy variable for Climate - sceptic President, which equals 1 when a president sceptical of climate change is elected. The model also incorporates financial variables such as Total Assets, Leverage, Return on Assets (ROA), Loan Loss Reserves relative to Gross Customer Loans, and Non-Interest Income relative to Operating Revenues. The analysis covers the period from the time each bank joined the Alliance through July 2025. At the bottom of the table, the number of observations and the number of clusters (financial institutions). Asterisks denote statistical significance: * at the 10% level, ** at the 5% level, and *** at the 1% level.

Dependent variable: Withdraw from NZBA	(1)	(2)	(3)	(4)	(5)
CRISK	-0.315***		-0.099		-0.089
	(0.058)		(0.061)		(0.058)
NZBA first target completion				0.266***	0.045***
				(0.032)	(0.009)
Climate - sceptic President		0.583***	0.577***		0.463***
		(0.020)	(0.020)		(0.029)
Total Assets (B$)	0.014***	0.018***	0.017***	0.005	0.013***
	(0.005)	(0.004)	(0.004)	(0.009)	(0.004)
Leverage	0.005***	0.001	0.001	0.010**	0.001
	(0.002)	(0.002)	(0.002)	(0.005)	(0.002)
ROA	0.011***	0.003	0.002	0.017*	0.001
	(0.006)	(0.004)	(0.004)	(0.009)	(0.004)
Loan loss reserves relative to gross customers loans & advances	-0.011***	-0.004***	-0.004**	-0.010**	-0.003*
	(0.003)	(0.001)	(0.001)	(0.004)	(0.001)
Non - interest income relative to operating revenues	0.000	0.000	0.000	0.000	0.000
	(0.000)	(0.000)	(0.000)	(0.000)	(0.000)
Observations	4,074	4,074	4,074	4,074	4,074
Number of banks	85	85	85	85	85

5.5. Conclusion

This study analyses climate risk, institutional responses to climate change, and the political and financial factors influencing these dynamics, with a particular focus on the Net-Zero Banking Alliance (NZBA). Our findings advance the literature on climate-related financial risks by delivering several key insights. First, within NZBA members, variation in short-term climate risk exposure does not appear to be systematically associated with membership alone. These results should be interpreted as descriptive patterns, suggesting that affiliation alone does not correspond to observable differences in climate risk over the short period examined. Instead, the results point to the importance of translating commitments into concrete actions and meeting clearly defined interim targets. Among NZBA members, banks that are further from their initial milestones tend to exhibit higher measured climate risk, highlighting within-member variation in CRISK rather than demonstrating a causal effect of milestone progress. Among the factors considered, the election of a climate-sceptical president emerges as an important driver of banks' climate risk, including for Global Systemically Important Banks (G-SIBs). This finding indicates that, among NZBA members, variation in climate risk is closely associated with political developments, while traditional financial metrics show less consistent patterns. Our analysis of NZBA withdrawal patterns indicates that the election of a climate-sceptical president is associated with an increased likelihood of exit—by roughly 54%—consistent with recent withdrawals by major U.S. and Japanese banks following political transitions. Taken together, these dynamics suggest that voluntary climate coalitions remain particularly sensitive to political environments.

The implications of our findings carry significant weight for policymakers and financial regulators: political shifts have the potential to undermine large banks climate-related priorities. While these withdrawals do not appear to affect the immediate stability of member banks, the patterns indicate that future political changes could be associated with changes in engagement with initiatives such as the NZBA. Within the short time window examined, many globally systemically important members show limited short-term progress toward reducing emissions and aligning portfolios with a net-zero trajectory by 2050, underscoring the preliminary and descriptive nature of these findings.

Our analysis focuses solely on banks participating in the NZBA, which limits identification due to the absence of a non-member control group. Nevertheless, the sample is highly representative of the global banking system, encompassing more than 60% of systemically important banks. Future research that includes non-member banks would be valuable for validating these findings.

Some additional concerns may arise that, due to the inherent nature of the data and analysis, cannot be fully resolved; however, they merit brief discussion. One limitation of the analysis is the relatively short time window and the high concentration of NZBA bank entries and exits within this period. As a result, the findings should be interpreted as preliminary and primarily descriptive. While they provide valuable initial insights into the potential determinants and consequences of NZBA participation, caution is warranted in generalizing the results, as longer-term dynamics, delayed effects, or additional political events may not yet be fully captured. Future research with extended time horizons will be necessary to establish more robust evidence.

Another general concern is that, although the analysis indicates a reduction in banks' climate risk following the achievement of the first targets, this coincides with a period of heightened attention to climate and sustainability, which may itself influence the result. Another limitation is that the measure of banks' climate risk used may not fully capture long-term structural exposures and instead reflects short-term market perceptions. Nonetheless, it can be considered the most reliable measure in the literature (Jung et al., 2025). In contrast, the measure of financed emissions has an annual temporal span, limited to the post-Paris Agreement period, and is available for only a restricted number of banks within the alliance. Lastly, the relatively recent establishment of the NZBA means that the analysis relies on a short panel with limited post-commitment data, which could introduce bias towards larger banks. However, given the robustness of the variable related to the election of a climate-sceptical President across the models proposed, it appears that political pressure may be the primary determining factor in these cases.

Several avenues for future research emerge from this analysis. For instance, the withdrawals observed to date have predominantly involved large, globally systemically banks. It is reasonable to question whether smaller financial institutions will eventually follow this trend. If smaller banks maintain their commitments, this raises a compelling question: why do political dynamics exert a stronger influence on the climate strategies of major banks while smaller institutions appear more resilient in upholding net-zero targets through 2050? Possible explanations include reduced political pressure on smaller banks, or a longer timeline for meeting interim targets that intensifies in the medium term, allowing these banks to adopt a more relaxed stance in the short run. Moreover, the withdrawal of Japanese banks from the NZBA, likely influenced by spillover effects stemming from political pressure on these institutions, underscores the need for a more comprehensive analysis. Future research should investigate global spillover models to better account for these interdependencies, particularly in the context of exogenous political factors across countries. Additionally, incorporating metrics such as the presence of U.S. nationals on bank boards, and the degree of economic interdependence with the United States market could yield valuable insights into Japan's banks' strategic dynamics, which notably differ from those observed in Europe.

Lastly, it could be interesting to examine the significance of reputational risk associated with climate risk within this context. Assuming that reputational risk is indeed a factor, what impact did the immediate withdrawal from the alliance have on this risk profile? Understanding the market's response would be valuable in this regard. On one hand, a positive reaction may suggest that banks are taking their membership in the Alliance seriously; in this case, they might prefer to withdraw in light of substantial political pressure rather than pursue a course that contradicts their commitments. Conversely, the market may interpret this withdrawal as indicative of a deterioration in reputational risk, recognizing that exiting the NZBA and the policies enacted in recent years are likely to lead to increased emissions and exacerbate climate risk.

APPENDIX TO CHAPTER 5

Figure A. 5. 1: Banks' emissions financing

This figure shows the annual proxy for banks' emissions financing for the three largest U.S. banks (JPMorgan, Citigroup, and Bank of America), along with the sample-wide average over the period 2016–2024. Values are expressed in billions of U.S. dollars. Markers identify the year of the first NZBA target achievement for each of the three banks.

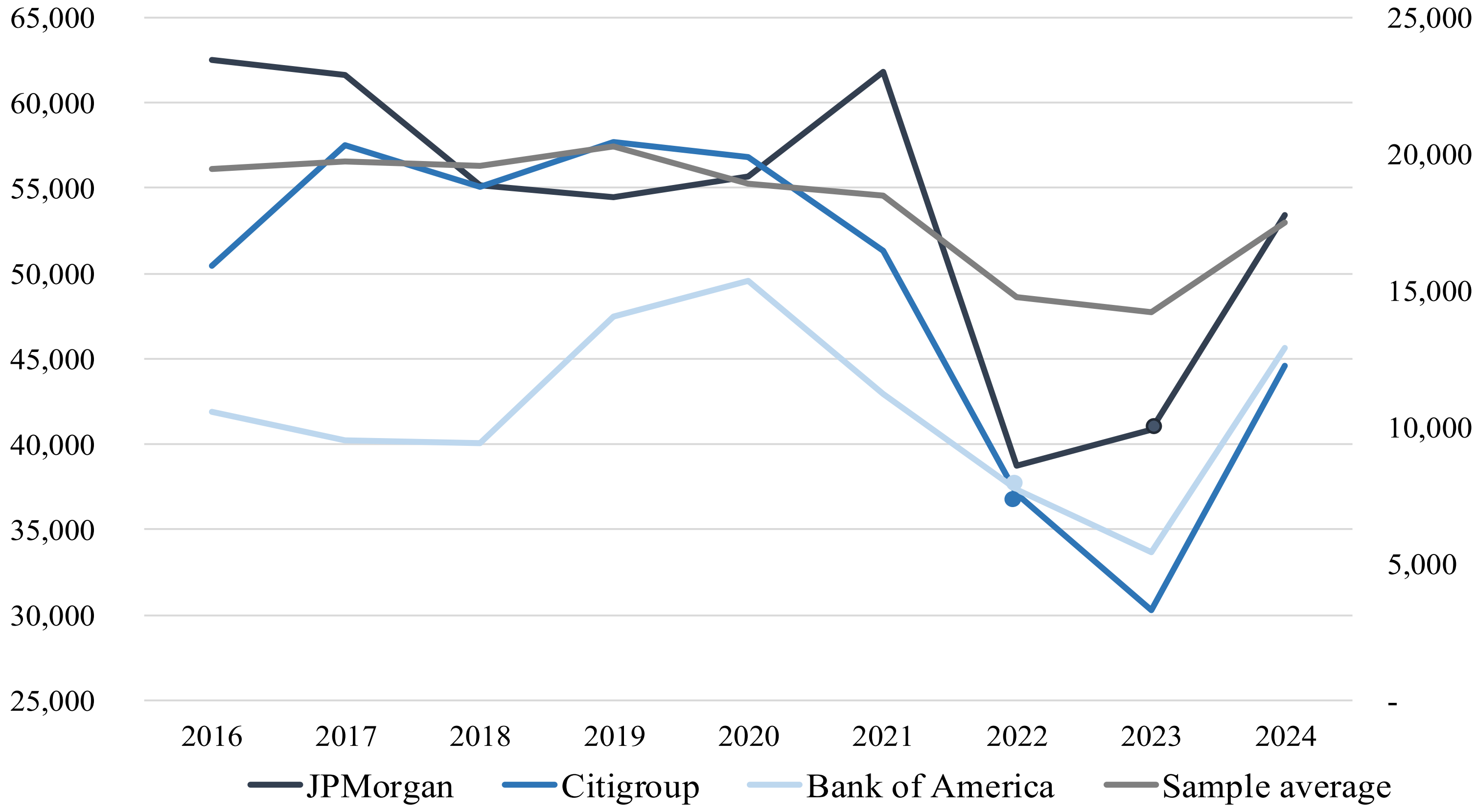

Table A. 5.1: Determinants of climate risk with geographic fixed effects — institutional, political, economic, and financial factors

This table reports the estimation results from the panel regression specified in Equation (18), with ΔCRISK as the dependent variable, which quantifies the monthly change in the climate risk indicator developed by Jung et al. (2025). Differently from the main results, we include regional and country-based fixed effects. The explanatory variables encompass institutional factors associated with NZBA membership, including a dummy variable for Joining NZBA (set to 1 from the month the bank joins), Distance from NZBA first target (representing the monthly distance to the first target), and a dummy for NZBA first target completion (equal to 1 from the month the bank achieves its initial goals). The variable Climate - sceptic President is a dummy that takes the value of 1 when a president sceptical of climate change is elected. Additionally, the Global Financial Crisis, Paris Agreement, and COVID Pandemic are dummy variables that equal 1 during their respective periods. The model further incorporates financial variables, including Total assets, Leverage, ROA, Loan loss reserves relative to gross customer loans, and Non-interest income relative to operating revenues. The Lagged CRISK variable is included to account for persistent effects, and all regressions control for fixed effects related to financial institutions, utilizing monthly observations from June 2000 to July 2025. At the bottom of the table, the number of observations, fixed effects, the number of clusters (financial institutions), and adjusted R-squared values are provided, with robust standard errors clustered at the bank level. Asterisks denote significance levels: * indicates significance at the 10% level, ** at the 5% level, and *** at the 1% level.

Dependent variable: ΔCRISK	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)
Joining NZBA	-0.598**	-0.490*	-0.422	-0.309	-0.381	-0.263	-0.261	-0.141
	(0.284)	(0.278)	(0.353)	(0.355)	(0.436)	(0.438)	(0.405)	(0.408)
Distance from NZBA first target	0.029*	0.032**	0.023*	0.026**	0.035**	0.038**	0.033*	0.036**
	(0.015)	(0.015)	(0.012)	(0.012)	(0.017)	(0.017)	(0.018)	(0.018)
NZBA first target completion	-0.422	-0.386	-0.448*	-0.411	-0.394	-0.356	-0.347	-0.308
	(0.260)	(0.259)	(0.272)	(0.271)	(0.333)	(0.332)	(0.357)	(0.356)
Climate - sceptic President		4.597***		4.613***		4.684***		4.748***
		(0.739)		(0.761)		(0.791)		(0.805)
Global financial crisis	1.726***	1.727***	1.942***	1.943***	2.637***	2.638***	2.816***	2.817***
	(0.501)	(0.501)	(0.624)	(0.624)	(0.886)	(0.887)	(0.914)	(0.915)
Paris agreement	0.430	-4.170***	0.313	-4.308***	0.772	-3.924***	0.664	-4.098***
	(0.415)	(0.749)	(0.550)	(0.961)	(0.742)	(1.134)	(0.763)	(1.207)
Covid pandemic	-3.040***	-3.446***	-2.903***	-3.309***	-2.501***	-2.913***	-2.372***	-2.789***
	(0.552)	(0.603)	(0.496)	(0.544)	(0.462)	(0.500)	(0.461)	(0.497)
Total assets	0.396*	0.397*	0.227	0.229	0.480	0.481	1.045	1.049
	(0.212)	(0.212)	(0.299)	(0.299)	(0.667)	(0.668)	(0.797)	(0.797)
Leverage	0.020	0.020	0.044	0.044	0.059	0.059	0.083	0.083
	(0.029)	(0.029)	(0.039)	(0.039)	(0.060)	(0.060)	(0.054)	(0.055)
ROA	-0.081	-0.077	-0.134*	-0.127*	-0.353**	-0.346**	-0.262**	-0.254**
	(0.063)	(0.063)	(0.075)	(0.075)	(0.149)	(0.148)	(0.125)	(0.124)
Loan loss reserves / gross customers loans & advances	0.014	0.014	0.011	0.011	0.034	0.034	0.030	0.030
	(0.016)	(0.016)	(0.015)	(0.015)	(0.027)	(0.027)	(0.026)	(0.026)
Non - interest income / Operating revenues	0.001	0.001	-0.003	-0.003	0.007	0.007	0.001	0.001
	(0.009)	(0.009)	(0.006)	(0.006)	(0.007)	(0.007)	(0.008)	(0.008)
Lagged CRISK	-0.020***	-0.020***	-0.035***	-0.035***	-0.081***	-0.081***	-0.093***	-0.093***
	(0.006)	(0.006)	(0.009)	(0.009)	(0.018)	(0.018)	(0.019)	(0.019)
Constant	-0.978**	-0.991**	-1.474***	-1.482***	-1.358*	-1.361*	-2.215***	-2.227***
	(0.409)	(0.409)	(0.553)	(0.554)	(0.731)	(0.731)	(0.611)	(0.612)
Observations	19,869	19,869	19,869	19,869	19,869	19,869	19,869	19,869
Year FE	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes
Region FE	Yes	Yes	No	No	No	No	No	No
Country FE	No	No	Yes	Yes	No	No	No	No
Bank FE*Country FE	No	No	No	No	Yes	Yes	No	No
Bank FE*Region FE	No	No	No	No	No	No	Yes	Yes
Adj R-squared	0.031	0.031	0.042	0.042	0.053	0.053	0.054	0.054
Number of banks	85	85	85	85	85	85	85	85

Table A. 5.2: Determinants of climate risk with banks' environmental score — institutional, political, economic, and financial factors

This table reports the estimation results from the panel regression specified in Equation (18), with ΔCRISK as the dependent variable, which quantifies the monthly change in the climate risk indicator developed by Jung et al. (2025). Differently from the main results, we include the bank's environmental score as an additional explanatory variable. The explanatory variables encompass institutional factors associated with NZBA membership, including a dummy variable for Joining NZBA (set to 1 from the month the bank joins), Distance from NZBA first target (representing the monthly distance to the first target), and a dummy for NZBA first target completion (equal to 1 from the month the bank achieves its initial goals). The variable Climate - sceptic President is a dummy that takes the value of 1 when a president sceptical of climate change is elected. Additionally, the Global Financial Crisis, Paris Agreement, and COVID Pandemic are dummy variables that equal 1 during their respective periods. The model further incorporates financial variables, including Total assets, Leverage, ROA, Loan loss reserves relative to gross customer loans, and Non-interest income relative to operating revenues. The Lagged CRISK variable is included to account for persistent effects, and all regressions control for fixed effects related to financial institutions, utilizing monthly observations from January 2006 to March 2025. At the bottom of the table, the number of observations, fixed effects, the number of clusters (financial institutions), and adjusted R-squared values are provided, with robust standard errors clustered at the bank level. Asterisks denote significance levels: * indicates significance at the 10% level, ** at the 5% level, and *** at the 1% level.

Dependent variable: ΔCRISK	(1)	(2)	(3)	(4)	(5)	(6)	(7)
Bank environmental score	0.330	0.343	0.242	0.250	0.206	0.331	0.213
	(0.373)	(0.373)	(0.372)	(0.374)	(0.370)	(0.373)	(0.370)
Joining NZBA		0.187			-0.191		-0.052
		(0.447)			(0.519)		(0.523)
Distance from NZBA first target			0.040**		0.037*		0.040*
			(0.016)		(0.020)		(0.020)
NZBA first target completion				-0.865**	-0.316		-0.273
				(0.334)	(0.396)		(0.395)
Climate - sceptic President						5.137***	5.273***
						(0.869)	(0.924)
Global financial crisis	4.220***	4.222***	4.223***	4.219***	4.221***	4.221***	4.224***
	(1.453)	(1.455)	(1.453)	(1.453)	(1.455)	(1.454)	(1.456)
Paris agreement	0.531	0.450	1.447*	1.401*	1.778*	-4.612***	-3.538***
	(0.850)	(0.893)	(0.855)	(0.814)	(0.935)	(1.165)	(1.196)
Covid pandemic	-2.345***	-2.303***	-2.239***	-2.348***	-2.291***	-2.821***	-2.741***
	(0.517)	(0.515)	(0.501)	(0.517)	(0.514)	(0.551)	(0.541)
Total assets	0.919	0.919	0.928	0.931	0.932	0.929	0.942
	(1.585)	(1.586)	(1.585)	(1.581)	(1.583)	(1.586)	(1.584)
Leverage	0.142	0.143	0.132	0.132	0.129	0.141	0.128
	(0.103)	(0.104)	(0.102)	(0.101)	(0.103)	(0.103)	(0.103)
ROA	-0.229	-0.227	-0.240	-0.241	-0.245*	-0.220	-0.235
	(0.145)	(0.143)	(0.147)	(0.146)	(0.145)	(0.143)	(0.144)
Loan loss reserves relative to gross customers loans & advances	0.043	0.043	0.050	0.049	0.052	0.042	0.051
	(0.035)	(0.035)	(0.035)	(0.035)	(0.035)	(0.035)	(0.035)
Non - interest income relative to Operating revenues	-0.004	-0.004	-0.004	-0.004	-0.004	-0.004	-0.004
	(0.012)	(0.012)	(0.012)	(0.012)	(0.012)	(0.012)	(0.012)
Lagged CRISK	-0.111***	-0.111***	-0.111***	-0.111***	-0.111***	-0.111***	-0.111***
	(0.025)	(0.026)	(0.025)	(0.025)	(0.026)	(0.026)	(0.026)
Constant	-5.374***	-5.436***	-5.011***	-5.018***	-4.846***	-5.392***	-4.901***
	(1.813)	(1.826)	(1.801)	(1.826)	(1.820)	(1.813)	(1.823)
Observations	14,982	14,982	14,982	14,982	14,982	14,982	14,982
Year FE	Yes	Yes	Yes	Yes	Yes	Yes	Yes
Bank FE	Yes	Yes	Yes	Yes	Yes	Yes	Yes
Adj R-squared	0.0641	0.0640	0.0642	0.0642	0.0641	0.0648	0.0648
Number of banks	78	78	78	78	78	78	78

Table A. 5.3: Probability of withdrawal from the NZBA with banks' environmental score

This table presents the estimation results from the logit regression outlined in Equation (19), with the dependent variable being the decision to withdraw from the Net Zero Banking Alliance (NZBA). Differently from the main results, we include the bank's environmental score as an additional explanatory variable. The explanatory variables include the bank's CRISK measure, the Distance from NZBA's first target (indicating the monthly distance to that target), and a dummy variable for a Climate - sceptic President, which equals 1 when a president sceptical of climate change is elected. Additionally, the model incorporates financial variables such as Total Assets, Leverage, Return on Assets (ROA), Loan Loss Reserves relative to Gross Customer Loans, and Non-Interest Income relative to Operating Revenues. The analysis covers the period from the time each bank joined the Alliance through July 2025. At the bottom of the table, the number of observations, the number of clusters (financial institutions), and adjusted R-squared values are displayed. Asterisks indicate significance levels: * for the 10% level, ** for the 5% level, and *** for the 1% level.

Dependent variable: Withdraw from NZBA	(1)	(2)	(3)	(4)	(5)	(6)
CRISK		-0.313***		-0.094		-0.087
		(0.060)		(0.061)		0.058
Bank environmental score	0.034	0.039	0.012	0.012	0.023	0.006
	(0.027)	(0.027)	(0.016)	(0.016)	0.036	0.015
NZBA first target completion					0.248***	0.042***
					(0.032)	0.010
Climate - sceptic President			0.588***	0.582***		0.480***
			(0.021)	(0.021)		0.030
Total Assets (B$)	0.017***	0.014***	0.017***	0.017***	0.005	0.013***
	(0.005)	(0.005)	(0.004)	(0.004)	0.008	0.004
Leverage	0.007**	0.008***	0.001	0.001	0.010**	0.001
	(0.003)	(0.003)	(0.002)	(0.002)	(0.005)	0.002
ROA	0.024***	0.020***	0.006	0.005	0.023**	0.002
	(0.006)	(0.006)	(0.004)	(0.004)	(0.010)	0.004
Loan loss reserves relative to gross customers loans & advances	-0.019***	-0.016***	-0.005**	-0.005**	-0.012**	-0.003
	(0.004)	(0.004)	(0.002)	(0.002)	(0.005)	0.002
Non - interest income relative to Operating revenues	0.000	0.000	0.000	0.000	0.000	0.000
	(0.000)	(0.000)	(0.000)	(0.000)	0.000	0.000
Observations	3,737	3,737	3,737	3,737	3,737	3,737
Number of banks	78	78	78	78	78	78

Table A. 5.4: Determinants of climate risk — financed emissions, institutional, political, economic, and financial factors

This table presents the estimation results from the panel regression specified in Equation (18), where ΔCRISK is the dependent variable, measuring the monthly change in the climate risk indicator developed by Jung et al. (2025). Differently from the main analysis, we add the one-year lagged bank's financed emissions (in millions of U.S. dollars) as an explanatory variable. Additional explanatory variables include institutional factors related to NZBA membership: a dummy variable for Joining NZBA (equal to 1 starting from the month the bank joins), Distance from NZBA's first target (indicating the number of months to the initial target), and a dummy for NZBA first target completion (equal to 1 from the month the bank meets its initial goals). The variable Climate - sceptic President is a dummy equal to 1 when a president sceptical of climate change is elected. Additional dummy variables represent the COVID-19 pandemic, each equal to 1 during the pandemic period. Financial control variables include Total assets, Leverage, Return on Assets (ROA), Loan loss reserves relative to gross customer loans, and Non-interest income relative to operating revenues. The model also includes Lagged CRISK to capture persistence in climate risk. All regressions include fixed effects for financial institutions and use monthly data from December 2016, when financed emissions data become available, to July 2025. At the bottom of the table, we report the number of observations, bank and year fixed effects, the number of clusters (financial institutions), and adjusted R-squared values. Robust standard errors are clustered at the bank level. Asterisks denote statistical significance: * at the 10% level, ** at the 5% level, and *** at the 1% level.

Dependent variable: ΔCRISK	(1)	(2)	(3)	(4)	(5)	(6)
Joining NZBA	-1.246			-0.399		0.183
	(1.242)			(1.779)		(1.810)
Distance from NZBA's first target		-0.056		-0.082		-0.064
		(0.045)		(0.080)		(0.080)
NZBA first target completion			-1.826**	-2.497**		-2.321*
			(0.801)	(1.167)		(1.172)
Climate - sceptic President					9.887***	9.570***
					(1.828)	(1.980)
Bank's financed emissions	0.110	0.115	0.101	0.111	0.110	0.111
	(0.095)	(0.097)	(0.096)	(0.097)	(0.097)	(0.098)
Covid pandemic	-3.767***	-3.595***	-3.411***	-3.785***	-4.351***	-4.470***
	(0.782)	(0.742)	(0.710)	(0.781)	(0.685)	(0.742)
Total assets	1.440	1.514	1.326	1.419	1.763	1.721
	(6.813)	(6.764)	(6.822)	(6.750)	(6.892)	(6.847)
Leverage	-1.492	-1.458	-1.537	-1.556	-1.427	-1.502
	(1.526)	(1.536)	(1.542)	(1.535)	(1.541)	(1.544)
ROA	-0.188	-0.259	-0.236	-0.225	-0.032	-0.042
	(1.190)	(1.177)	(1.165)	(1.218)	(1.130)	(1.177)
Loan loss reserves relative to gross customers loans & advances	0.005	0.003	0.020	0.020	0.008	0.021
	(0.049)	(0.049)	(0.046)	(0.045)	(0.048)	(0.045)
Non - interest income relative to Operating revenues	-0.011	-0.012	-0.010	-0.011	-0.012	-0.011
	(0.041)	(0.040)	(0.042)	(0.041)	(0.042)	(0.041)
Lagged CRISK	-0.170***	-0.171***	-0.170***	-0.170***	-0.171***	-0.171***
	(0.033)	(0.033)	(0.032)	(0.032)	(0.033)	(0.033)
Constant	1.432	1.143	1.900	1.768	-9.232	-8.503
	(13.383)	(13.425)	(13.504)	(13.386)	(14.124)	(14.010)
Observations	3,157	3,157	3,157	3,157	3,157	3,157
Year FE	Yes	Yes	Yes	Yes	Yes	Yes
Bank FE	Yes	Yes	Yes	Yes	Yes	Yes
Adj R-squared	0.094	0.094	0.094	0.094	0.096	0.096
Number of banks	31	31	31	31	31	31

Table A. 5.5: Factors influencing withdrawal from the Net Zero Banking Alliance (NZBA), including banks' financed emissions

This table presents the estimation results from the logit regression specified in Equation (19), where the dependent variable is the decision to withdraw from the Net-Zero Banking Alliance (NZBA). Differently from the main analysis, we add the one-year lagged bank's financed emissions (in millions of U.S. dollars) as an explanatory variable. Additional explanatory variables include the bank's CRISK measure, and a dummy variable for Climate - sceptic President, which equals 1 when a president sceptical of climate change is elected. The model also incorporates financial variables such as Total Assets, Leverage, Return on Assets (ROA), Loan Loss Reserves relative to Gross Customer Loans, and Non-Interest Income relative to Operating Revenues. The analysis covers the period from the time each bank joined the Alliance through July 2025. At the bottom of the table, the number of observations and the number of clusters (financial institutions). Asterisks denote statistical significance: * at the 10% level, ** at the 5% level, and *** at the 1% level.

Dependent variable: Withdraw from NZBA	(1)	(2)	(3)	(4)	(5)
CRISK		-0.001***			0.000**
		(0.000)			(0.000)
Climate - sceptic President				0.666***	0.029**
				(0.033)	(0.013)
Distance from NZBA first target			-0.015***		-0.013***
			(0.002)		(0.003)
Bank's financed emissions	0.002***	0.002***	0.004***	0.002***	0.004***
	(0.001)	(0.001)	(0.001)	(0.001)	(0.001)
Total Assets (B$)	0.000	0.000***	0.000***	0.000***	0.000*
	(0.000)	(0.000)	(0.000)	(0.000)	(0.000)
Leverage	-0.006	0.000	0.001	0.001	-0.003
	(0.008)	(0.011)	(0.007)	(0.002)	(0.005)
ROA	0.033	-0.004	0.036	0.003	0.063**
	(0.023)	(0.015)	(0.025)	(0.004)	(0.028)
Loan loss reserves relative to gross customers loans & advances	-0.019*	-0.079***	-0.022	-0.004***	-0.029**
	(0.011)	(0.029)	(0.012)	(0.001)	(0.014)
Non - interest income relative to operating revenues	0.000	0.000	-0.001	0.000	-0.002***
	(0.000)	(0.000)	(0.000)	(0.000)	(0.000)
Observations	1,525	1,525	1,525	1,525	1,525
Number of banks	31	31	31	31	31

Table A. 5.6: Determinants of climate risk of G-SIBs — institutional, political, economic, and financial factors

This table reports the estimation results from the panel regression specified in Equation (18), with ΔCRISK as the dependent variable, which quantifies the monthly change in the climate risk indicator developed by Jung et al. (2025). Differently from the main results, we restrict the analysis to Globally Systemically Important Banks (G-SIBs). The explanatory variables encompass institutional factors associated with NZBA membership, including a dummy variable for Joining NZBA (set to 1 from the month the bank joins), Distance from NZBA first target (representing the monthly distance to the first target), and a dummy for NZBA first target completion (equal to 1 from the month the bank achieves its initial goals). The variable Climate - sceptic President is a dummy that takes the value of 1 when a president sceptical of climate change is elected. Additionally, the Global Financial Crisis, Paris Agreement, and COVID Pandemic are dummy variables that equal 1 during their respective periods. The model further incorporates financial variables, including Total assets, Leverage, ROA, Loan loss reserves relative to gross customer loans, and Non-interest income relative to operating revenues. The Lagged CRISK variable is included to account for persistent effects, and all regressions control for fixed effects related to financial institutions, utilizing monthly observations from June 2000 to July 2025. At the bottom of the table, the number of observations, fixed effects, the number of clusters (financial institutions), and adjusted R-squared values are provided, with robust standard errors clustered at the bank level. Asterisks denote significance levels: * indicates significance at the 10% level, ** at the 5% level, and *** at the 1% level.

Dependent variable: ΔCRISK	(1)	(2)	(3)	(4)	(5)	(6)
Joining NZBA	-2.849**			-2.046		-1.311
	(1.248)			(2.366)		(2.346)
Distance from NZBA first target		-0.105*		-0.081		-0.058
		(0.051)		(0.123)		(0.123)
NZBA first target completion			-1.661*	-2.353*		-2.152*
			(0.890)	(1.153)		(1.156)
Climate - sceptic President					10.458***	9.460***
					(1.448)	(1.416)
Global financial crisis	7.062**	7.087**	7.077**	7.071**	7.078**	7.073**
	(2.736)	(2.739)	(2.735)	(2.740)	(2.736)	(2.741)
Paris agreement	0.590	-3.205	1.465	0.442	-10.689***	-8.798**
	(2.010)	(2.670)	(2.078)	(4.519)	(1.950)	(4.164)
Covid pandemic	-6.053***	-5.518***	-5.152***	-6.084***	-6.143***	-6.669***
	(1.381)	(1.494)	(1.444)	(1.384)	(1.486)	(1.428)
Total assets	0.571	0.654	0.591	0.587	0.626	0.604
	(1.710)	(1.704)	(1.720)	(1.688)	(1.714)	(1.688)
Leverage	0.757	0.727	0.745	0.747	0.730	0.736
	(0.569)	(0.571)	(0.574)	(0.560)	(0.572)	(0.559)
ROA	-1.587	-1.591	-1.583	-1.587	-1.559	-1.562
	(0.988)	(0.998)	(0.992)	(0.992)	(0.983)	(0.983)
Loan loss reserves / gross customers loans & advances	0.297	0.300	0.301	0.297	0.299	0.296
	(0.228)	(0.229)	(0.229)	(0.230)	(0.227)	(0.228)
Non - interest income / Operating revenues	-0.013	-0.014	-0.013	-0.013	-0.013	-0.013
	(0.020)	(0.019)	(0.020)	(0.019)	(0.020)	(0.019)
Lagged CRISK	-0.103***	-0.104***	-0.103***	-0.103***	-0.103***	-0.103***
	(0.018)	(0.018)	(0.018)	(0.018)	(0.018)	(0.018)
Constant	-6.055*	-5.899*	-6.021*	-6.013*	-5.972*	-5.995*
	(3.194)	(3.226)	(3.207)	(3.169)	(3.208)	(3.165)
Observations	5,558	5,558	5,558	5,558	5,558	5,558
Year FE	Yes	Yes	Yes	Yes	Yes	Yes
Bank FE	Yes	Yes	Yes	Yes	Yes	Yes
Adj R-squared	0.0679	0.0677	0.0676	0.0681	0.0687	0.0689
Number of banks	23	23	23	23	23	23

Table A. 5.7: Probability of withdrawal from the NZBA of Globally Systemically Important Banks

This table presents the estimation results from the panel logit regression outlined in Equation (19), with the dependent variable being the decision to withdraw from the Net Zero Banking Alliance (NZBA). Differently from the main results, we restrict the analysis to Globally Systemically Important Banks (G-SIBs). The explanatory variables include the bank's CRISK measure, the Distance from NZBA's first target (indicating the monthly distance to that target), and a dummy variable for Climate - sceptic President, which equals 1 when a president sceptical of climate change is elected. Additionally, the model incorporates financial variables such as Total Assets, Leverage, Return on Assets (ROA), Loan Loss Reserves relative to Gross Customer Loans, and Non-Interest Income relative to Operating Revenues. The analysis covers the period from the time each bank joined the Alliance through July 2025. At the bottom of the table, the number of observations, the number of financial institutions, and pseudo R-squared values are displayed. Asterisks indicate significance levels: * for the 10% level, ** for the 5% level, and *** for the 1% level.

Dependent variable: Withdraw from NZBA	(1)	(2)	(3)	(4)	(5)
CRISK	-0.001***		-0.000***		0.000
	(0.000)		(0.000)		(0.000)
Distance from NZBA first target				-0.019*	-0.016**
				(0.010)	(0.007)
Climate - sceptic President		0.713***	0.689***		0.030*
		(0.046)	(0.041)		(0.016)
Total Assets (B$)	0.344***	0.010	0.008	0.007	0.015
	(0.098)	(0.008)	(0.007)	(0.013)	(0.016)
Leverage	-0.010	0.016**	0.015	0.040**	0.041**
	(0.016)	(0.007)	(0.006)	(0.018)	(0.018)
ROA	0.046	0.013	-0.038	0.059	0.079*
	(0.029)	(0.025)	(0.028)	(0.055)	(0.043)
Loan loss reserves relative to gross customers loans & advances	-0.053	-0.002	0.002	-0.004	-0.007
	(0.039)	(0.010)	(0.009)	(0.020)	(0.017)
Non - interest income relative to Operating revenues	0.001	0.000	0.000	0.000	0.000
	(0.000)	(0.000)	(0.000)	(0.001)	(0.001)
Observations	1,037	1,037	1,037	1,037	1,037
Number of banks	21	21	21	21	21

6. Conclusions

6.1. Summary of the findings and limitations

Chapter 3 examines how risk inherent in syndicated lending, specifically through leveraged and covenant-lite loans, translates into systemic risk for the banking sector. These loan types, characterised by lower borrower protections and higher leverage, have become increasingly prevalent, raising concerns among regulators and financial stability boards. Drawing on the methodology proposed by Blickle et al. (2020), this study uses granular data from the U.S. syndicated loan market to estimate the degree to which such exposures contribute to systemic risk, measured via the systemic risk measure SRISK. The analysis finds that leveraged and covenant-lite loans, in isolation, do not inherently increase systemic risk. However, their effects become significant during periods of economic stress, when “pipeline risk” materializes—i.e., when banks are forced to hold onto loans that cannot be syndicated under deteriorating market conditions. This effect is especially pronounced for institutions with higher retained shares in syndicated deals. It points to an amplification mechanism based on market liquidity and balance sheet inflexibility. Moreover, while the overall interconnectedness of the syndicated loan market has declined in recent years, the centrality of systemically important banks has increased. This concentrated exposure suggests heightened vulnerability to cascading failures should any one of these core institutions experience distress. These findings provide important insights into the dynamics of systemic risk transmission in modern credit markets. However, the study is limited by its geographical scope and data constraints. The analysis focuses solely on the U.S. market, which is the most developed and well-documented syndicated loan environment globally. Applying this framework to European or Asian banking systems would require methodological adjustments, particularly because the Blickle et al. approach relies on assumptions about post-origination loan behaviour and market structure that may not hold outside the U.S. context.

Chapter 4 introduces climate risk as an additional layer of systemic vulnerability within the syndicated loan market. The findings demonstrate a consistent and statistically significant negative relationship between banks' environmental lending quality and their systemic risk, suggesting that markets view banks with more sustainable credit portfolios as more resilient to climate-related shocks. Furthermore, physical climate risk, including both short-term anomalies and extreme events, is positively associated with systemic risk, especially in high-exposure regions. However, the significance of physical risks diminishes when policy-driven climate risks are introduced, suggesting that regulatory uncertainty is a primary transmission channel of climate-related financial vulnerability. Despite its novel contributions, this chapter faces two main limitations. The first is the lack of a standardized, high-coverage, environmental score data across borrowers and regions. ESG data quality varies substantially between providers, and many firms lack full coverage, especially in emerging markets. This limits the accuracy of the climate-adjusted portfolio metric and may introduce measurement errors that attenuate the observed relationships. Additionally, the regulatory index employed focuses primarily on major policy announcements and may not fully capture subtle but impactful changes. The second limitation concerns the use of the borrower's headquarters location as a proxy for the geographic region of their principal activities. Although the literature provides mixed evidence on the reliability of this approach (see, for example, Jiménez et al., 2009; Gao et al., 2011; Ling et al., 2021), in the context of climate risk analysis this assumption is particularly sensitive. It is plausible that some borrowers face climate-related risks in regions other than, or entirely different from, the location of their headquarters, particularly when their operations are geographically dispersed and include substantial subsidiaries in other parts of the United States or abroad. Such a gap between the registered location and the actual operational footprint may result in an underestimation or misclassification of the bank's true exposure to climate risks. This is particularly the case when the exposure is evaluated through the borrower-weighted composition of its syndicated loan portfolio.

Chapter 5 focuses on voluntary climate initiatives, specifically the Net-Zero Banking Alliance (NZBA). It finds that NZBA membership is associated with a reduction in climate risk, indicating that markets reward tangible climate commitments. However, the chapter also highlights the fragility of such initiatives, particularly their vulnerability to political interference. Political leadership changes in the U.S. are found to be a significant predictor of NZBA withdrawal, raising concerns about the long-term resilience of these coalitions. A key limitation of this analysis lies in capturing the intent and credibility behind banks' climate pledges, which may not correspond to real implementation efforts. Furthermore, national election outcomes may only partially reflect the broader political pressures banks experience.

6.2. Suggestions for future research

Future research could seek to replicate the systemic risk methodology used in ***Chapter 3*** in non-U.S. jurisdictions. Comparing markets across jurisdictions provides insight into how the unique features of each financial system influence the way systemic risk travels. In the United States, syndicated loans are typically built on the standardized templates of the Loan Syndications and Trading Association (LSTA), and they trade in a highly active secondary market that enables risk to move quickly between institutional investors. In much of Europe, the Loan Market Association (LMA) framework is the norm, but contracts can vary more from country to country, and secondary trading is generally thinner. These differences could shape both the pace and the routes through which financial stress spreads. Also, some European countries have highly concentrated banking systems, which can lead to more intense but narrower shocks, while the U.S. banking market is more competitive and diffuse.

Attempting to replicate the analysis of Blickle et al. (2022) in the European context would offer a valuable chance to examine the syndicated loan market within the world's second-largest region by loan issuance volume. Applying the model to Europe's diverse and multifaceted market environment would allow researchers to test whether the original findings hold consistently outside the U.S., or whether region-specific factors lead to different outcomes. For instance, the way European banks manage the selling or distribution of loans after origination may follow different methods compared to their U.S. counterparts, influenced by distinct regulatory frameworks, market practices, or investor behaviours. These variations could affect how risks are transferred and concentrated across financial institutions, potentially altering the patterns of systemic risk propagation identified in the original study. Exploring such differences would deepen our understanding of the interconnectedness and vulnerabilities within European credit markets, while also contributing to the refinement of systemic risk models on a global scale.

Building on the findings of ***Chapter 4***, future research should aim to incorporate more detailed and region-specific regulatory indicators to better capture the full range of policy-driven climate risks faced by banks. In particular, a new study could extend beyond analysing the immediate, short-term effects of climate-related policies to also examine their medium- and long-term impacts. This broader temporal perspective would provide valuable insights into how banks adjust and adapt over time to evolving regulatory landscapes, shedding light on the duration and dynamics of their response to climate policy changes. An especially important factor to consider would be the periods following U.S. presidential elections, given the sharply contrasting climate policy approaches observed under different administrations to date. These election cycles introduce distinct phases of policy uncertainty and shifts that likely influence banks' climate risk management strategies and their capacity to anticipate or respond to regulatory changes. By focusing on these politically driven transitions, future work could better understand the timing and intensity of banks' adaptation processes, offering a more nuanced view of how political cycles intersect with climate risk in the financial sector.

Additionally, conducting a similar analysis focused on the European Union, which is widely recognised as a leader in climate awareness and the development of comprehensive climate policies, could provide valuable insights into how different regulatory frameworks shape the transmission of climate-related financial risks. The considerable diversity among European countries, reflected in their distinct approaches to climate regulation, enforcement intensity, and financial market structures, offers a natural laboratory to rigorously test and validate how these policies influence banks' risk exposures and adaptation strategies. This national heterogeneity allows for an in-depth examination of how climate policies, varying in timing and strictness, differently impact the financial system. It also helps identify the conditions under which such policies are most effective in mitigating climate-related risks. Moreover, a comparative analysis within the European Union can reveal the mechanisms through which climate strategies spread among member states and highlight the crucial role played by European institutions in coordinating and harmonizing these efforts at the regional level. For example, significant differences in clean energy production exist between countries like Italy, which remains heavily reliant on traditional energy sources, and Sweden, where the energy system is largely based on renewables and nuclear power. These disparities not only shape national policy priorities but also influence how the banking sector assesses and manages climate risks, creating varied scenarios of exposure and resilience.

To deepen the analysis presented in ***Chapter 5***, future research would greatly benefit from incorporating qualitative methods such as case studies, interviews, or surveys. These approaches can provide richer insights into banks' internal decision-making processes and the external factors influencing their participation, or withdrawal, from voluntary climate initiatives. By exploring the motivations, challenges, and organizational dynamics behind these decisions, researchers can uncover nuances that purely quantitative analyses may overlook. Furthermore, exploring why smaller banks in North America have largely chosen not to follow the withdrawal trend from the Net-Zero Banking Alliance (NZBA) observed among the largest institutions would complement this study. This divergence could stem from a variety of causes. It may reflect lower political exposure for smaller banks. Alternatively, it could indicate that smaller banks are slower to react to political changes or shifts in the regulatory environment. Understanding this distinction is critical because it would shed light on how bank size influences climate commitment dynamics and adaptation timing. Although the NZBA target applies to all banks by 2050, small and medium-sized banks may implement it more slowly, making them less affected by sudden political changes like new presidential administrations.

The coordinated withdrawal of five out of six major Japanese banks from the Net-Zero Banking Alliance (NZBA) also warrants closer examination. It is essential to determine whether these decisions were primarily politically motivated or strategic responses to anticipated regulatory changes, especially in key markets like the United States. In this context, the strong dependence of Japan on raw materials sourced from the U.S., alongside the introduction of tariffs and other trade measures, may have significantly influenced the banks' strategic choices. A thorough analysis could reveal whether these decisions were driven mainly by domestic political pressures, international market considerations, or broader geopolitical dynamics.

Another crucial aspect for future analysis is to assess to what extent achieving the Net-Zero Banking Alliance (NZBA) targets has actually resulted in a measurable reduction of exposure to high-impact sectors within climate finance. A focused investigation could uncover potential greenwashing practices, meaning that despite banks' formal commitments or withdrawals following U.S. presidential election outcomes, there may be little evidence of substantial structural portfolio changes. This would suggest that the sector remains highly sensitive to political shifts, and that, in reality, many banks were not genuinely moving their portfolios toward net-zero alignment prior to these political events. Conversely, the analysis could also confirm current positive findings, demonstrating that meeting the NZBA targets does indeed correspond to a real decrease in banks' climate risk exposures. In such cases, this would indicate that the banks were actively transitioning their lending and investment portfolios toward net-zero emissions targets, thereby reducing their vulnerability to climate-related financial risks.

In conclusion, given that the green energy market, such as the solar sector, appears largely unaffected by recent political changes, future research could explore this resilience. It could also examine how banks, despite ongoing incentives to hold significant shares in fossil fuel companies, have made progress in recognizing the need to hedge against climate risks, regardless of the political changes. This progress, however, may be accompanied by a form of "greenhushing", whereby institutions intentionally reduce the visibility of their climate-related actions to avoid political scrutiny or controversy. Investigating this phenomenon could help reveal the gap between banks' public climate commitments and their actual portfolio management, shedding light on how political frameworks shape the challenges of implementing genuine climate risk mitigation within the financial sector.

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