

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

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## Abstract

This study examines how climate risks influence systemic risk through the U.S. syndicated loan market. It combines eight established climate risk measures with a new proxy for banks' environmentally friendly orientation, along with sixteen region-specific indicators capturing short-term anomalies, long-term drought conditions, and extreme events. The analysis identifies four key drivers of systemic risk: banks' environmental stance, extreme events in the South, precipitation anomalies in the East, and shifts in U.S. climate policy. The findings indicate that while banks are exposed to risks arising from climate-sensitive regions, environmentally friendly lending contributes to greater stability. However, current climate policies are not effectively reducing uncertainty, and stronger policies are needed to promote sustainable lending and support financial stability, particularly in the Southern and Eastern regions.

JEL classification: G21, Q51, Q54.

Keywords: Climate risk, systemic risk, syndicated loans.

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## 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.<sup>1</sup> 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 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

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<sup>1</sup> See for reference Figure 1 – *Financial risks from climate risk drivers* in *Climate-related risk drivers and their transmission channels* (BCBS, 2021).

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 environmentally friendly 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 strengthen 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.<sup>2</sup> 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 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.

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<sup>2</sup> 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.

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.<sup>3</sup> 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 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

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<sup>3</sup> 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.

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<sup>4</sup>, 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 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<sup>5</sup> 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

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<sup>4</sup> 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)

<sup>5</sup> 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 CO2 emission information of the organization.

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 2 outlines the methodology used in this study, and Section 3 presents the data utilized for our analysis. Section 4 presents the primary empirical findings along with robustness tests, and Section 5 concludes the paper.

## **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.

### **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 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 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.

### 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:

$$Environmentally\_friendly\_index_{i,t} = \frac{\sum_{j,k,t} Loan\ environemtally-weighte\ amount_{i,j,k,t}}{\sum_{j,k,t} Loan\ environemtally-weight\ amount_{j,k,t}} \quad (1)$$

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.

### 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:

$$\begin{aligned} & \text{Temperature regional – weighted index}_{i,k,t} = \\ & = \text{Regional temperature anomaly}_{k,t} \times \frac{\text{Lender regional amount}_{i,k,t}}{\text{Lender market amount}_{i,t}}, \end{aligned} \quad (2)$$

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:

$$\begin{aligned}
& PDSI \text{ regional} - \text{weighted index}_{i,k,t} = \\
& = \text{Regional PDSI}_{k,t} \times \frac{\text{Lender regional amount}_{i,k,t}}{\text{Lender market amount}_{i,t}},
\end{aligned}
\tag{3}$$

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:

$$\begin{aligned}
& \text{Extreme regional} - \text{weighted impact costs}_{i,k,t} = \\
& = \text{Extreme regional impact costs}_{k,t} \times \frac{\text{Lender regional amount}_{i,k,t}}{\text{Lender market amount}_{i,t}},
\end{aligned}
\tag{4}$$

## 2.2. 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:

$$\begin{aligned}
& SRISK = E(k(D + MV) - MV \mid \text{Crisis}) = \\
& = kD - (1 - k)(1 - LRMES)MV,
\end{aligned}
\tag{5}$$

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, 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:

$$SN\_RISK_{i,t}^{Lev\&CovLite} = \frac{Lev_{i,t} + Lev\&CovLite_{i,t} + CovLite_{i,t}}{Lev_t + Lev\&CovLite_t + CovLite_t}, \quad (6)$$

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 include the lender's size measured as Total Assets in billion dollars (\$) <sup>6</sup>; the Market Size of the syndicated loan market in billion dollars; and the one-period lagged *SRISK*.

### 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:

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<sup>6</sup> 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.

$$\begin{aligned}
\Delta SRISK_{i,t} = & \alpha + \beta_1(Environmmentally\_friendly\_index_{i,t-1}) \\
& + \beta_2(Western\ temperature\ regional - weighted\ index_{i,t-1}) \\
& + \beta_3(Western\ precipitation\ regional - weighted\ index_{i,t-1}) \\
& + \beta_4(Eastern\ temperature\ regional - weighted\ index_{i,t-1}) \\
& + \beta_5(Eastern\ precipitation\ regional - weighted\ index_{i,t-1}) \\
& + \beta_6(Central\ temperature\ regional - weighted\ index_{i,t-1}) \\
& + \beta_7(Central\ temperature\ regional - weighted\ index_{i,t-1}) \\
& + \beta_8(Southern\ temperature\ regional - weighted\ index_{i,t-1}) \\
& + \beta_9(Southern\ temperature\ regional - weighted\ index_{i,t-1}) \\
& + \beta_{10}(Western\ PDSI - weighted\ index_{i,t-1}) \\
& + \beta_{11}(Eastern\ PDSI - weighted\ index_{i,t-1}) \\
& + \beta_{12}(Central\ PDSI - weighted\ index_{i,t-1}) \\
& + \beta_8(Southern\ PDSI - weighted\ index_{i,t-1}) \\
& + \beta_9(Western\ extreme - weighted\ impact\ cost_{i,t-1}) \\
& + \beta_{10}(Eastern\ extreme - weighted\ impact\ cost_{i,t-1}) \\
& + \beta_{11}(Central\ extreme - weighted\ impact\ cost_{i,t-1}) \\
& + \beta_{12}(Southern\ extreme - weighted\ impact\ cost_{i,t-1}) \\
& + \beta_{10}(SN\_RISK_{i,t-1} * USRecession_t) \\
& + \beta_{11}(SN\_RISK_{i,t-1} * USNon - Recession_t) \\
& + \beta_{12}(Interconnectedness_{i,t-1} * USRecession_t) \\
& + \beta_{13}(Interconnectedness_{i,t-1} * USNon - Recession_t) \\
& + \beta_{14}(TotalAssets_{i,t-1}) \\
& + \beta_{15}(MarketSize_{i,t-1}) \\
& + \beta_{16}(LaggedSRISK_{i,t-1}) + FixedEffects_i + \varepsilon_{i,t}
\end{aligned}
\tag{7}$$

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 *Environmmentally\_friendly\_index* 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. Additionally, we incorporate commonly used control variables from the literature (Cai et al., 2018; Sina et al., 2025), lagged by one month. These include lenders' interconnectedness, total assets (in billions of dollars), market share, the market size of the syndicated loan market (in billions of dollars), and the one-period lag of SRISK. 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 3.3.

### 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.<sup>7</sup> To build the final dataset for the empirical analysis we use a combination of automated and manual matching techniques.

#### 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.<sup>8</sup> Table 2 presents the distribution of syndicated loan amounts issued by four major lenders—JPMorgan, Bank of America, Citi, and Wells Fargo—

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<sup>7</sup> 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 indicators for recession and non-recession periods, provided by the National Bureau of Economic Research (NBER).

<sup>8</sup> 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.

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 2). In terms of industrial sectors (Panel B of Table 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 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,<sup>9</sup> providing a valuable subset for analysis.

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

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<sup>9</sup> 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>.

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 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.

### 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 summarizes temperature data, precipitation data, and the Palmer Drought Severity Index for the four regions<sup>10</sup>: 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, the Southern region has the highest average temperature at 63.33°F, indicating it is warmer than the other regions. This is especially

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<sup>10</sup> 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>

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 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, 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 characterizes 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.

Table 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, totaling \$41 billion from 2013 to 2022, which accounts for 5.0% of the total extreme weather costs in the U.S.

### 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.<sup>11</sup> 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 gathered monthly, extending through June 2017 for the WSJ index and May 2018 for the second index.<sup>12</sup>

To account for unexpected increases in climate change concerns, we use the Media Climate Change Concerns Index from Ardia et al. (2023)<sup>13</sup>, 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.<sup>14</sup> 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,

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<sup>11</sup> The metric is available at the following link: <https://osf.io/fd6jq/files/osfstorage>

<sup>12</sup> Both indices are available at the following link:

<https://drive.google.com/file/d/1pCHmcebmOwrVCFim78ALhB51c3h1qt2T/view?pli=1>

<sup>13</sup> The index is available at the following link: <https://sentometrics-research.com/>

<sup>14</sup> The indexes are available at the following link:

[https://docs.google.com/spreadsheets/d/1JW7l\\_ZLCsPm7wP0rSaEZzMedZJ7M2opK/edit?pli=1&gid=793134818#gid=793134818](https://docs.google.com/spreadsheets/d/1JW7l_ZLCsPm7wP0rSaEZzMedZJ7M2opK/edit?pli=1&gid=793134818#gid=793134818)

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. 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 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*. This indicates that banks engaged in financing environmentally-friendly projects within the U.S. 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*. 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 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. The results show a significant positive relationship between these climate risks and how stable banks are perceived to be. In the Eastern U.S., the analysis shows that more rainfall is associated with a greater perception of risk among banks. This is especially relevant since this region often experiences weather events like heavy rains and cyclones. The results for the Western region are robust in Table 6 but not across all robustness tests, despite wildfire-related costs having increased by over 1,000% in the past 20 years, highlighting the importance for banks to consider these climate-related risks in their lending practices. In models [8] to [11], we also include the Palmer Drought Severity Index (PDSI) in our

regression analysis. The weighted PDSI shows a positive and statistically significant effect for the central region in all models. This suggests that long-term drought conditions might affect systemic risk for banks. However, we don't see a similar significant effect with short-term climate anomalies. This difference could be because the PDSI is a long-term measure that accounts for ongoing drought conditions, capturing their lasting impact. As the central region largely relies on agriculture, persistent drought conditions could make banks more sensitive to prolonged climate impacts on borrowers' creditworthiness.

In addition to climate-risk factors, each regression model includes elements from previous studies that help explain differences in lenders' systemic risk, and our findings support those earlier results (Cai et al., 2018; Sina et al., 2025). The relationship between interconnectedness, measured using network-based metrics, and whether the economy is in a recession aligns with the literature. Specifically, the results indicate that when banks are more interconnected during recessions, systemic risk tends to increase. Moreover, the findings show that syndication risk has a bigger impact on systemic risk during economic downturns than in stable times. The results in Table 6 also show that larger banks are more vulnerable to systemic risk, confirming what earlier studies have found (Cai et al., 2018; Laeven et al., 2016; Sedunov, 2016, Sina et al., 2025).

Overall, our findings in Table 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 can increase 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 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 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 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 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.

In contrast, models [6] and [7] of Table 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.

#### 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.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.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.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.

## 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.

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.<sup>15</sup> Several studies demonstrate that these risks can interact and amplify each other (López et al., 2025;

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<sup>15</sup> See for reference the website <https://climate.sustainability-directory.com/term/compound-climate-risk/>

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.

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## Tables

**Table 1: Climate risk variable description**

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

| <b>Variable name</b>                            | <b>Source</b>                                                       | <b>Description</b>                                                                                                                                                                                                                                                                                                                                                                                                                                                                         |
|-------------------------------------------------|---------------------------------------------------------------------|--------------------------------------------------------------------------------------------------------------------------------------------------------------------------------------------------------------------------------------------------------------------------------------------------------------------------------------------------------------------------------------------------------------------------------------------------------------------------------------------|
| <i>Environmentally_friendly_index</i>           | Thomson Reuters Eikon and self-calculation                          | The <i>Environmentally_friendly_index</i> 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 <i>Temperature regional-weighted index</i> 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 <i>Precipitation regional-weighted index</i> 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 <i>Extreme regional-weighted index</i> 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 1 - continues in the next page)

(Table 1 - continued)

|                                                                                                                 |                                                                                                                                                                                                                                                                 |                                                                                                                                                                                                                                                                                                                                                                                                                                                                    |
|-----------------------------------------------------------------------------------------------------------------|-----------------------------------------------------------------------------------------------------------------------------------------------------------------------------------------------------------------------------------------------------------------|--------------------------------------------------------------------------------------------------------------------------------------------------------------------------------------------------------------------------------------------------------------------------------------------------------------------------------------------------------------------------------------------------------------------------------------------------------------------|
| CCExposure_lender_index                                                                                         | Sautner et al. (2023):<br><a href="https://osf.io/fd6jq/files/osfstorage">https://osf.io/fd6jq/files/osfstorage</a><br>and self-calculation                                                                                                                     | The <i>CCExposure_lender_index</i> primarily utilizes the <i>CCExposure index</i> 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 <i>CCExposure_lender_index</i> 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):<br><a href="https://drive.google.com/file/d/1pCHmcebmOwrVCFim78ALhB51c3h1qt2T/view">https://drive.google.com/file/d/1pCHmcebmOwrVCFim78ALhB51c3h1qt2T/view</a>                                                                             | The <i>Wall Street Journal (WSJ) climate change news index</i> 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):<br><a href="https://drive.google.com/file/d/1pCHmcebmOwrVCFim78ALhB51c3h1qt2T/view">https://drive.google.com/file/d/1pCHmcebmOwrVCFim78ALhB51c3h1qt2T/view</a>                                                                             | The <i>Crimson Hexagon (CH) Negative climate change news index</i> 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):<br><a href="https://www.dropbox.com/s/jwjh4b08zvq09nv/LICENSE.txt?dl=0">https://www.dropbox.com/s/jwjh4b08zvq09nv/LICENSE.txt?dl=0</a>                                                                                                     | The <i>Media Climate Change Concerns index (MCCC)</i> 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):<br><a href="https://docs.google.com/spreadsheets/d/1JW71_ZLCsPm7wPOrSaEZzMedZJ7M2opK/edit?gid=1333933877#gid=1333933877">https://docs.google.com/spreadsheets/d/1JW71_ZLCsPm7wPOrSaEZzMedZJ7M2opK/edit?gid=1333933877#gid=1333933877</a> | 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).                                                                                                                                                                                                                                                                                 |

**Table 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.

| JPM                                                   |                                   |       | Bank of America |                                   |       | Citi  |                                   |       | Wells Fargo |                                   |       |
|-------------------------------------------------------|-----------------------------------|-------|-----------------|-----------------------------------|-------|-------|-----------------------------------|-------|-------------|-----------------------------------|-------|
| Panel A. Share distribution across U.S. states        |                                   |       |                 |                                   |       |       |                                   |       |             |                                   |       |
| 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 |                                   |       |                 |                                   |       |       |                                   |       |             |                                   |       |
| 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%  |

**Table 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

| <b>Industrial sectors</b>         | <b>N</b> | <b>Mean</b> | <b>SD</b> | <b>p10</b> | <b>p50</b> | <b>p90</b> |
|-----------------------------------|----------|-------------|-----------|------------|------------|------------|
| 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

| <b>United States</b> | <b>N</b>   | <b>Mean</b>  | <b>SD</b>    | <b>p10</b>   | <b>p50</b>   | <b>p90</b>   |
|----------------------|------------|--------------|--------------|--------------|--------------|--------------|
| 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        |
| <i>Other</i>         | <i>861</i> | <i>36.65</i> | <i>21.91</i> | <i>13.36</i> | <i>33.97</i> | <i>62.83</i> |

**Table 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<br>value (F°) | 52.35 | 15.50 | 31.65 | 52.58 | 73.70 |
| <i>of which New York</i>   |                           | 46.34 | 17.12 | 23.75 | 46.30 | 70.10 |
| Western                    |                           | 51.12 | 14.13 | 33.35 | 49.90 | 72.25 |
| <i>of which California</i> |                           | 59.35 | 11.86 | 44.45 | 58.15 | 77.55 |
| Central                    |                           | 47.86 | 17.92 | 22.70 | 48.33 | 72.80 |
| <i>of which Illinois</i>   |                           | 52.82 | 17.60 | 28.95 | 54.13 | 75.65 |
| Southern                   |                           | 63.33 | 13.17 | 45.35 | 63.60 | 81.20 |
| <i>of which Texas</i>      |                           | 66.04 | 13.23 | 47.90 | 66.45 | 84.10 |
| Eastern                    | Temperature<br>anomaly    | 1.64  | 2.89  | -1.85 | 1.50  | 6.35  |
| <i>of which New York</i>   |                           | 1.84  | 3.39  | -1.90 | 1.60  | 7.60  |
| Western                    |                           | 1.78  | 2.37  | -1.15 | 1.78  | 5.65  |
| <i>of which California</i> |                           | 1.97  | 2.38  | -1.10 | 2.10  | 5.85  |
| Central                    |                           | 1.48  | 3.22  | -2.50 | 1.50  | 6.90  |
| <i>of which Illinois</i>   |                           | 1.19  | 3.78  | -3.05 | 1.15  | 7.20  |
| Southern                   |                           | 1.27  | 2.28  | -1.40 | 1.08  | 5.25  |
| <i>of which Texas</i>      |                           | 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<br>value (mm) | 3.87  | 1.13 | 2.35  | 3.90  | 5.86 |
| <i>of which New York</i>   |                             | 3.71  | 1.34 | 2.13  | 3.49  | 6.08 |
| Western                    |                             | 1.66  | 0.87 | 0.71  | 1.49  | 3.52 |
| <i>of which California</i> |                             | 1.71  | 1.98 | 0.90  | 0.87  | 6.19 |
| Central                    |                             | 2.38  | 1.04 | 1.04  | 2.27  | 4.11 |
| <i>of which Illinois</i>   |                             | 3.44  | 1.64 | 1.48  | 3.30  | 6.77 |
| Southern                   |                             | 3.19  | 1.09 | 1.85  | 3.09  | 5.19 |
| <i>of which Texas</i>      |                             | 2.33  | 1.43 | 0.74  | 2.15  | 5.33 |
| Eastern                    | Precipitation<br>anomaly    | 0.26  | 1.03 | -1.01 | 0.22  | 2.17 |
| <i>of which New York</i>   |                             | 0.36  | 1.24 | -1.11 | 0.25  | 2.60 |
| Western                    |                             | -0.08 | 0.64 | -0.85 | -0.16 | 1.10 |
| <i>of which California</i> |                             | -0.16 | 1.46 | -1.98 | -0.14 | 2.54 |
| Central                    |                             | 0.14  | 0.64 | -0.62 | 0.08  | 1.25 |
| <i>of which Illinois</i>   |                             | 0.31  | 1.43 | -1.35 | 0.14  | 3.21 |
| Southern                   |                             | 0.09  | 1.00 | -1.09 | -0.07 | 1.97 |
| <i>of which Texas</i>      |                             | 0.08  | 1.32 | -1.38 | -0.22 | 2.81 |

(Table 4 - continues in the next page)

(Table 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  |
| <i>of which New York</i>   |              | 276 | 1.26  | 1.94 | -1.53 | 1.49  |
| Western                    |              | 276 | -1.83 | 2.43 | -4.30 | -2.49 |
| <i>of which California</i> |              | 276 | -1.78 | 2.63 | -4.85 | -2.30 |
| Central                    |              | 276 | 0.99  | 2.38 | -1.47 | 0.63  |
| <i>of which Illinois</i>   |              | 276 | 1.26  | 2.25 | -1.82 | 1.55  |
| Southern                   |              | 276 | -0.61 | 2.84 | -5.08 | -0.37 |
| <i>of which Texas</i>      |              | 276 | -0.90 | 3.11 | -4.48 | -1.23 |
| Eastern                    | PDSI anomaly | 276 | 0.61  | 2.21 | -2.06 | 0.80  |
| <i>of which New York</i>   |              | 276 | 1.28  | 1.94 | -1.52 | 1.45  |
| Western                    |              | 276 | -2.06 | 2.43 | -4.49 | -2.73 |
| <i>of which California</i> |              | 276 | -1.79 | 2.65 | -4.89 | -2.26 |
| Central                    |              | 276 | 0.59  | 2.38 | -1.91 | 0.21  |
| <i>of which Illinois</i>   |              | 276 | 1.23  | 2.25 | -1.92 | 1.52  |
| Southern                   |              | 276 | -0.72 | 2.84 | -5.16 | -0.52 |
| <i>of which Texas</i>      |              | 276 | -0.85 | 3.12 | -4.52 | -1.22 |

**Table 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 5 - continues in the next page)

(Table 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%         |

**Table 6: Relationship between systemic risk and climate risks**

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

(Table 6 - continues in the next page)

(Table 6 - continued)

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

**Table 7: Examining the connection between systemic risk and climate change risk through variables identified in existing literature**  
**(Engle et al., 2020; Ardia et al., 2023; Faccini et al., 2023; Sautner et al., 2023)**

This table displays the results of panel regressions based on Equation (7), with the dependent variable being the  $\Delta$ SRISK 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 3.3. 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 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 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: $\Delta$ SRISK                       | (1)                  | (2)                  | (3)                   | (4)                   | (5)                  | (6)                  | (7)                  | (8)                 | (9)                 |
|----------------------------------------------------------|----------------------|----------------------|-----------------------|-----------------------|----------------------|----------------------|----------------------|---------------------|---------------------|
| Environmentally_Friendly_Index                           |                      | -8.128*<br>(4.053)   | -15.417***<br>(4.820) | -13.579***<br>(4.872) | -8.325**<br>(3.577)  | -9.092**<br>(4.095)  | -9.071**<br>(4.073)  | -9.198**<br>(4.047) | -9.114**<br>(4.023) |
| CCExposure                                               | 0.083*<br>(0.044)    | 0.099<br>(0.064)     |                       |                       |                      |                      |                      |                     |                     |
| Wall Street Journal Climate Change News Index (log)      |                      |                      | 0.194<br>(0.234)      |                       |                      |                      |                      |                     |                     |
| Crimson Hexagon Negative Climate Change News Index (log) |                      |                      |                       | 0.183<br>(0.218)      |                      |                      |                      |                     |                     |
| Media Climate Change Concerns Index                      |                      |                      |                       |                       | -0.021<br>(0.327)    |                      |                      |                     |                     |
| U.S. climate policy                                      |                      |                      |                       |                       |                      | 0.239**<br>(0.092)   |                      |                     |                     |
| International summits                                    |                      |                      |                       |                       |                      |                      | 0.318*<br>(0.172)    |                     |                     |
| Global warming                                           |                      |                      |                       |                       |                      |                      |                      | -0.303<br>(0.237)   |                     |
| Natural disasters                                        |                      |                      |                       |                       |                      |                      |                      |                     | 0.079<br>(0.175)    |
| Constant                                                 | -1.822***<br>(0.527) | -2.619***<br>(0.937) | 1.396<br>(1.275)      | -2.076<br>(1.296)     | -1.870***<br>(0.684) | -2.299***<br>(0.795) | -2.393***<br>(0.850) | -2.049**<br>(0.857) | -2.236**<br>(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               |

## Appendix

**Table A.1: Regional share**

This table displays the results of panel regressions based on Equation (7), with the dependent variable being the  $\Delta$ SRISK 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 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 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: $\Delta$ SRISK            | (1)                  | (2)                  | (3)                  | (4)                  | (5)                  | (6)                  |
|-----------------------------------------------|----------------------|----------------------|----------------------|----------------------|----------------------|----------------------|
| Environmentally_Friendly_Index                | -8.299**<br>(3.629)  | -8.237**<br>(3.641)  | -7.124**<br>(3.177)  | -7.376**<br>(3.165)  | -7.243**<br>(3.172)  | -7.113**<br>(3.173)  |
| Western syndicated loans share                | -0.123<br>(0.397)    | -0.927<br>(0.561)    | -0.740<br>(0.543)    | 0.141<br>(0.447)     | -0.579<br>(0.487)    | -0.346<br>(0.450)    |
| Eastern syndicated loans share                | 0.265<br>(0.209)     | 0.033<br>(0.263)     | 0.061<br>(0.267)     | 0.327<br>(0.240)     | 0.066<br>(0.284)     | 0.053<br>(0.277)     |
| Central syndicated loans share                | 0.287<br>(0.255)     | 0.295<br>(0.256)     | 0.308<br>(0.262)     | 0.086<br>(0.231)     | 0.087<br>(0.271)     | 0.154<br>(0.283)     |
| Southern syndicated loans share               | 0.350<br>(0.257)     | 0.122<br>(0.294)     | 0.085<br>(0.304)     | 0.340<br>(0.261)     | 0.121<br>(0.297)     | 0.062<br>(0.308)     |
| Western PDSI-weighted anomaly index           |                      |                      |                      | 0.139<br>(0.126)     | 0.247<br>(0.161)     | 0.291*<br>(0.165)    |
| Eastern PDSI-weighted anomaly index           |                      |                      |                      | -0.065<br>(0.098)    | -0.058<br>(0.093)    | -0.005<br>(0.101)    |
| Central PDSI-weighted anomaly index           |                      |                      |                      | 0.177**<br>(0.084)   | 0.200**<br>(0.084)   | 0.155<br>(0.094)     |
| Southern PDSI-weighted anomaly index          |                      |                      |                      | -0.006<br>(0.063)    | 0.029<br>(0.061)     | 0.006<br>(0.059)     |
| Western temperature-weighted anomaly index    |                      | 0.513*<br>(0.268)    | 0.483*<br>(0.267)    |                      | 0.577**<br>(0.287)   | 0.562*<br>(0.287)    |
| Western precipitation-weighted anomaly index  |                      | 0.549<br>(0.408)     | 0.379<br>(0.420)     |                      | 0.270<br>(0.390)     | 0.089<br>(0.392)     |
| Eastern temperature-weighted anomaly index    |                      | 0.081<br>(0.067)     | 0.067<br>(0.067)     |                      | 0.092<br>(0.067)     | 0.078<br>(0.067)     |
| Eastern precipitation-weighted anomaly index  |                      | 0.301*<br>(0.177)    | 0.347*<br>(0.179)    |                      | 0.319*<br>(0.184)    | 0.355*<br>(0.186)    |
| Central temperature-weighted anomaly index    |                      | 0.029<br>(0.127)     | 0.010<br>(0.128)     |                      | 0.028<br>(0.126)     | 0.010<br>(0.127)     |
| Central precipitation-weighted anomaly index  |                      | -0.223<br>(0.407)    | -0.289<br>(0.429)    |                      | -0.384<br>(0.396)    | -0.383<br>(0.414)    |
| Southern temperature-weighted anomaly index   |                      | 0.143**<br>(0.060)   | 0.156**<br>(0.062)   |                      | 0.141**<br>(0.058)   | 0.153**<br>(0.059)   |
| Southern precipitation-weighted anomaly index |                      | -0.403<br>(0.248)    | -0.331<br>(0.249)    |                      | -0.381<br>(0.237)    | -0.303<br>(0.234)    |
| Western extreme-weighted impact cost          |                      |                      | 0.693**<br>(0.317)   |                      |                      | 0.669**<br>(0.332)   |
| Eastern extreme-weighted impact cost          |                      |                      | 0.419<br>(0.570)     |                      |                      | 0.446<br>(0.576)     |
| Central extreme-weighted impact cost          |                      |                      | -0.084<br>(0.488)    |                      |                      | -0.250<br>(0.528)    |
| Southern extreme-weighted impact cost         |                      |                      | 1.848**<br>(0.790)   |                      |                      | 1.760**<br>(0.779)   |
| Control variables                             | Yes                  | Yes                  | Yes                  | Yes                  | Yes                  | Yes                  |
| Constant                                      | -2.044***<br>(0.682) | -2.012***<br>(0.688) | -2.861***<br>(0.898) | -2.058***<br>(0.679) | -2.028***<br>(0.684) | -2.823***<br>(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.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 (7), with the dependent variable being the  $\Delta$ SRISK 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 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 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: $\Delta$ SRISK                  | (1)                  | (2)                  | (3)                  |
|-----------------------------------------------------|----------------------|----------------------|----------------------|
| Environmentally_Friendly_Index                      | -8.081**<br>(3.815)  | -8.105**<br>(3.801)  | -7.979**<br>(3.822)  |
| Lender_environmental_score                          | 0.011<br>(0.010)     | 0.012<br>(0.010)     | 0.011<br>(0.010)     |
| Western temperature-weighted anomaly index          | 0.346<br>(0.239)     |                      | 0.350<br>(0.233)     |
| Western precipitation-weighted anomaly index        | 0.718<br>(0.428)     |                      | 0.527<br>(0.449)     |
| Eastern temperature-weighted anomaly index          | 0.071<br>(0.060)     |                      | 0.065<br>(0.061)     |
| Eastern precipitation-weighted anomaly index        | 0.359*<br>(0.202)    |                      | 0.411*<br>(0.212)    |
| Central temperature-weighted anomaly index          | 0.075<br>(0.140)     |                      | 0.055<br>(0.141)     |
| Central precipitation-weighted anomaly index        | -0.364<br>(0.426)    |                      | -0.397<br>(0.438)    |
| Southern temperature-weighted anomaly index         | 0.162**<br>(0.067)   |                      | 0.173**<br>(0.066)   |
| Southern precipitation-weighted anomaly index       | -0.363<br>(0.346)    |                      | -0.337<br>(0.345)    |
| Western extreme-weighted impact cost                |                      | 0.640<br>(0.382)     | 0.649<br>(0.390)     |
| Eastern extreme-weighted impact cost                |                      | 0.272<br>(0.620)     | 0.298<br>(0.628)     |
| Central extreme-weighted impact cost                |                      | -0.183<br>(0.504)    | -0.132<br>(0.503)    |
| Southern extreme-weighted impact cost               |                      | 2.032**<br>(0.836)   | 2.000**<br>(0.849)   |
| Centrality $\times$ U.S. Recession                  | 0.191**<br>(0.084)   | 0.179**<br>(0.087)   | 0.187**<br>(0.087)   |
| Centrality $\times$ U.S. Non-recession              | -0.007<br>(0.040)    | -0.003<br>(0.041)    | 0.003<br>(0.040)     |
| $SN\_RISK^{Lev\&CovLite} \times$ U.S. Recession     | 0.711***<br>(0.218)  | 0.721***<br>(0.222)  | 0.717***<br>(0.224)  |
| $SN\_RISK^{Lev\&CovLite} \times$ U.S. Non-Recession | -0.081<br>(0.126)    | -0.087<br>(0.124)    | -0.084<br>(0.125)    |
| Total Assets (B\$)                                  | 0.002***<br>(0.000)  | 0.003***<br>(0.001)  | 0.003***<br>(0.001)  |
| Constant                                            | -2.861***<br>(0.952) | -3.575***<br>(1.138) | -3.698***<br>(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.3: The connection between systemic risk and ESG borrowers factors within lenders' portfolios**

This table displays the results of panel regressions based on Equation (7), with the dependent variable being the  $\Delta$ SRISK 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 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 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: $\Delta$ SRISK                             | (1)                  | (2)                  | (3)                  | (4)                  |
|----------------------------------------------------------------|----------------------|----------------------|----------------------|----------------------|
| ESG_Friendly_Index                                             | -9.285**<br>(4.578)  | -9.131*<br>(4.583)   | -9.162**<br>(4.571)  | -9.011*<br>(4.580)   |
| Western temperature-weighted anomaly index                     |                      | 0.319<br>(0.212)     |                      | 0.326<br>(0.209)     |
| Western precipitation-weighted anomaly index                   |                      | 0.598<br>(0.370)     |                      | 0.406<br>(0.385)     |
| Eastern temperature-weighted anomaly index                     |                      | 0.058<br>(0.050)     |                      | 0.056<br>(0.050)     |
| Eastern precipitation-weighted anomaly index                   |                      | 0.318*<br>(0.167)    |                      | 0.376**<br>(0.174)   |
| Central temperature-weighted anomaly index                     |                      | 0.071<br>(0.113)     |                      | 0.047<br>(0.113)     |
| Central precipitation-weighted anomaly index                   |                      | -0.263<br>(0.360)    |                      | -0.292<br>(0.374)    |
| Southern temperature-weighted anomaly index                    |                      | 0.151***<br>(0.050)  |                      | 0.157***<br>(0.050)  |
| Southern precipitation-weighted anomaly index                  |                      | -0.357<br>(0.247)    |                      | -0.310<br>(0.247)    |
| Western extreme-weighted impact cost                           |                      |                      | 0.666**<br>(0.300)   | 0.676**<br>(0.305)   |
| Eastern extreme-weighted impact cost                           |                      |                      | 0.379<br>(0.522)     | 0.383<br>(0.529)     |
| Central extreme-weighted impact cost                           |                      |                      | -0.156<br>(0.442)    | -0.144<br>(0.451)    |
| Southern extreme-weighted impact cost                          |                      |                      | 1.812**<br>(0.740)   | 1.794**<br>(0.749)   |
| Centrality $\times$ U.S. Recession                             | 0.176**<br>(0.072)   | 0.183**<br>(0.072)   | 0.167**<br>(0.076)   | 0.174**<br>(0.076)   |
| Centrality $\times$ U.S. Non-recession                         | -0.004<br>(0.034)    | 0.001<br>(0.033)     | 0.003<br>(0.034)     | 0.008<br>(0.033)     |
| SN_RISK <sup>Lev&amp;CovLite</sup> $\times$ U.S. Recession     | 0.722***<br>(0.196)  | 0.718***<br>(0.196)  | 0.734***<br>(0.202)  | 0.730***<br>(0.203)  |
| SN_RISK <sup>Lev&amp;CovLite</sup> $\times$ U.S. Non-Recession | -0.093<br>(0.119)    | -0.091<br>(0.120)    | -0.096<br>(0.119)    | -0.094<br>(0.119)    |
| Total Assets (B\$)                                             | 0.003***<br>(0.000)  | 0.003***<br>(0.000)  | 0.003***<br>(0.000)  | 0.003***<br>(0.000)  |
| Constant                                                       | -1.864***<br>(0.644) | -2.001***<br>(0.634) | -2.645***<br>(0.815) | -2.788***<br>(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                |