Climate Risk and Financial Stability: Evidence from Bank Lending

Thomas Conlon[a], Rong Ding[b], Xing Huan[c,*], Zhifang Zhang[c]

[a]*Smurfit Graduate Business School, University College Dublin, Ireland.*
[b]*Neoma Business School, France.*
[c]*Warwick Business School, University of Warwick, United Kingdom.*

Abstract

We study the impact of climate risk on banks' tail risks and systemic risk contribution. Employing climate risk measures developed using the Billion-Dollar Weather and Climate Disasters data from National Oceanic and Atmospheric Administration (NOAA) and Dealscan syndicated lending data, we find that banks' climate risk exposure acquired through the lending channel increases their tail risks and systemic risk contribution. Our results are robust to an instrumental variables approach, several alternative climate risk and systemic risk measures, and a variety of model specifications. We contribute to a growing literature on the impact climate risk on financial stability and the development towards robust measures of climate risk for banks.

Keywords: bank lending, climate change, climate risk, financial stability, systemic risk

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*Corresponding author, Email: xing.huan@wbs.ac.uk, Telephone: +44 (0)24 7652 2173

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1. Introduction

What we have known simply as "climate change" for the past thirty five years is now a global crisis. According to World Economic Forum (2021), climate action failure, extreme weather conditions, and environmental damage arising from human activities are among the most likely risks that the world will be exposed to over the next decade. Regulators have paid close attention to climate change and its implications for financial stability.[1] Central banks and financial regulators have started to design scenarios for climate stress tests to gauge how vulnerable the financial system is to climate change. Despite the sense of urgency and policy significance of this topic, considerable gaps remain in the academic research. A major challenge facing both climate finance researchers and practitioners is the shortage of methodologies that facilitate robust measurement of climate risk and promote a successful assessment of the impact of climate change on financial stability (Bank for International Settlements, 2021; Battiston *et al.*, 2021). The aim of this paper is to make progress in this matter through developing a method to calibrate climate risk and to examine its impact on financial stability.

Prior studies document the effects of climate risks on both financial and nonfinancial firms. Firms that are more exposed to extremely high temperatures suffer lower revenues and operating income (Pankratz *et al.*, 2019). Climate risk is negatively associated with earnings of publicly listed firms and positively associated with their earnings and cash flows volatility, which further influences firm capital structure: firms in countries with higher climate risk tend to hold more long-term debt and cash while paying lower cash

[1]For example, the Financial Stability Board's (FSB) Task Force on Climate-related Financial Disclosures (TCFD) released its recommendations on climate risk management and disclosure for financial institutions in June 2017 with the objective of developing voluntary disclosure on climate risk. In November 2017, the Economic and Monetary Affairs Committee (EMAC) of the European Parliament issued a proposal that would amend the European Union's Capital Requirements Regulation to make climate risk management and disclosures mandatory. In July 2021, the FSB drew up a roadmap for addressing climate-related financial risks, which highlights four key interconnected blocks namely disclosures, data, vulnerabilities analysis, and regulatory practices and tools.

dividends (Huang *et al.*, 2017). Battiston *et al.* (2017) examine how climate policies affect revenues and costs for different sectors in the real economy with indirect effects on financial sectors. They find that the combined exposure to climate policy-relevant sectors is large and heterogeneous, and financial sectors are directly exposed to climate policy-relevant sectors. A further strand of literature focuses on banks' reaction to climate change, primarily reflected in the price discrimination embedded in loan pricing. Delis *et al.* (2019) show that banks started pricing climate policy risk by charging marginally higher loan rates to fossil fuel firms after 2015. Javadi and Masum (2021) document that firms in locations with higher exposure to climate risk pay significantly higher spreads on their bank loans. Similarly, Jiang *et al.* (2020) find that lender banks impose a higher cost of credit for fossil fuel firms that are subject to stricter climate policies and for firms exposed to greater sea level rise (SLR) risk. The awareness of the SLR risk is also reflected in prices in residential mortgage markets (Nguyen *et al.*, 2022).

Climate risk would appear to meet the minimal definition of a systemic risk proposed by Benoit *et al.* (2017), as the risk that many market participants are simultaneously affected by severe losses, which then spread through the system. Significant variation in levels of systemic risk has been determined conditional on the institution's noninterest income (Brunnermeier *et al.*, 2020), corporate governance (Anginer *et al.*, 2018), jurisdiction (Bostandzic and Weiss, 2018), size (Laeven *et al.*, 2016; Pais and Stork, 2013), competition (Anginer *et al.*, 2014), network interdependence (Hautsch *et al.*, 2015), capital (Gauthier *et al.*, 2012) and the provision of government aid (Berger *et al.*, 2020). Despite the previously described catalyst for climate risk to contribute to bank systemic risk; however, only limited empirical support has been furnished.

Two main channels of risk transmission from climate change to financial stability have been identified: physical risks and transition risks. Physical climate risks arise when climate change causes damage to physical assets and disruption to operations of firms, generating increased credit risk for lender banks, increasing claims for insurance companies, and impairing the financial position of governments. Transition climate risks relate to unanticipated and sudden adjustments of asset prices (both positive and negative) and changes in default rates for entire asset classes due to shifts in policies, technology, and sentiment in the process of adjustment towards a low-carbon economy (Financial Stability Board, 2020). In this paper, we focus on physical climate risks.

Physical climate risks adversely affect banks in two primary ways. First, physical climate risks can directly cause damage to physical assets and accelerate depreciation of capital assets, for example, through its connection with extreme weather events such as flood, storm, or wildfire. Such impact can be offset as insurance generally covers losses due to unexpected catastrophic events. Second, a more relevant impact comes from the fact that physical climate risks can change (usually reduce) the outputs achievable with a given level of inputs, which amounts to a change in the return on capital assets. Banks' credit risk increases and loan quality declines when borrower firms' ability to repay loans is weakened by climate risk events. Dietz *et al.* (2016) document that the estimate of the impact of climate change on asset value (i.e., climate value at risk or climate VaR) is economically significant and mostly distributed in the tail. More importantly, it is difficult to model and to hedge climate risks given the unexpected nature and the long horizon over which such risks may materialize (Financial Stability Board, 2020).

We first create a bank-level climate risk measure using the Billion-Dollar Weather and Climate Disasters data from National Oceanic and Atmospheric Administration (NOAA) and Dealscan syndicated lending data. We then employ this measure to examine the effect of banks' climate risk exposure on their tail risks and systemic risk contribution based on a sample of 7,830 lender-borrower-year observations comprised of 31 lender banks and 1,778 borrower firms for the period of 1999–2017. Our identification strategy consists of three key elements: (1) lender bank and borrower firm fixed effects to control for latent constant characteristics of banks and borrowers as well as loan demand around loan origination, allowing variation in the bank-level climate risk measure to explain the remaining variation; (2) controlling of book value of loans (i.e., loan ratios) to filter out the incremental effect from syndicated lending; and (3) an instrumental variables approach that avails an exogenous source of variation in the bank-level climate risk. We find that banks' climate risk exposure acquired through the lending channel increases their tail risks and systemic risk contribution. This effect is both statistically and economically significant: An increase by one standard deviation in the bank-level climate risk measure leads to an increase of 3.1% in tail risk at 5%, 8.0% in tail risk at 1%, 8.7% in the marginal expected shortfall, 2.5% in the long-run marginal expected shortfall, 0.4% in systemic risk contribution at 5%, and 0.9% in systemic risk contribution at 1%. We perform additional tests and find that the results are robust to several alternative climate risk measures including an adjusted climate risk measure accounting for borrowers' vulnerability to climate change, a residual climate risk measure that is orthogonal to common bank risk factors, and an alternative climate risk measure computed following the Germanwatch method. Our results also hold with interaction tests that decompose the climate risk measure, with an alternative method to estimate systemic risk, with weighted least squares estimators, and with alternative methods to compute standard errors.

This paper makes several contributions. First, we contribute to the literature on systemic risk by documenting borrower firms' exposure to climate risk as a source for lender banks' systemic risk contribution. Second, we contribute to the literature on climate risk by proposing a climate risk measure that quantifies the extent to which banks have suffered direct losses due to extreme weather events such as storms, floods, heat waves, and wildfire. In contrast to the other climate risk measures that focus on, for example, heat exposure (Pankratz *et al.*, 2019), or the sea level rise (Nguyen *et al.*, 2022; Jiang *et al.*, 2020; Bernstein *et al.*, 2019), our measure captures the direct impact of economic losses due to climate change. We believe that this set of measures can create an avenue for future research that seeks to examine the impact of climate change on different aspects of social and economic life. Lastly, this paper is relevant to regulators' ongoing efforts in measuring climate risks and understanding their implications for financial stability, which also provide validation on central banks' involvement in safeguarding monetary and financial stability against climate change.

The remainder of the paper is organized as follows. Section 2 describes the data and approach employed to measure climate risk. Section 3 presents the empirical design. Section 4 presents baseline results. Section 5 reports robustness results. Section 6 concludes.

2. Measuring Climate Risk

2.1. Data

We use the Billion-Dollar Weather and Climate Disasters Data from the National Centers for Environmental Information (NCEI) database maintained by NOAA to measure the state-level climate risk. We employ extreme weather event data as physical climate risk is mostly driven by severe weather events (Li *et al.*, 2020). The NCEI database reports weather and climate disasters where overall losses equaled or exceeded $1 billion. Climate risk events are classified into seven disaster categories: drought, flooding, freeze, severe storm, tropical cyclone, wild fire, and winter storm. For the 1980–2020 reporting cycle, it reports 290 events with total human deaths of 14,492 and total losses exceeding $1.98 trillion[2], corresponding to an average of seven events and 353 deaths per year and a loss of $6.8 billion per event (NOAA, 2020).

We map the raw climate risk loss data to provide an overview of the variation in climate risk across the states. Figure 1 displays the cumulative losses due to climate risk

[2]CPI-adjusted to 2020.

events during the period of 1980–2020. Figure 2 maps the total number of climate risk events for the same period. Georgia, Mississippi, North Carolina, and Texas are among the high-risk states in terms of both loss severity and frequency over the years.

[Figure 1 and 2 about here.]

We collect data on syndicated loans from the Dealscan database maintained by the Loan Pricing Corporation (LPC). Dealscan provides comprehensive information on syndicated loans at origination, including loan amount, maturity, pricing, and identity of lenders and borrowers. A syndicated loan is facilitated by a syndicate of lenders jointly providing funding to a single borrower. The unit of observation in the Dealscan database is a facility (or tranche). A typical syndicated loan deal (or package) consists of multiple facilities initiated at the same time. A deal is arranged by sole or a few lead lenders who solicit the syndicated members and define the lending arrangement. We use the largest facility to represent the deal[3] and retain lead arrangers for each deal. Lead arrangers hold a larger loan share for signaling purposes (Sufi, 2007), make the loan pricing decisions, and are liable to reputational costs if they misprice loans. Following Bharath *et al.* (2011), we designate a bank as a lead arranger if the bank is the sole lender or the lender role is reported as *admin agent*, *agent*, *arranger*, or *lead bank* in Dealscan.

We restrict our analysis to credit lines and term loans made by US banks to domestic nonfinancial firms. We focus on credit lines and term loans because they are the dominant types of loans made by banks to nonfinancial firms (Colla *et al.*, 2013; Jiang *et al.*, 2010; Sufi, 2009). Following Chu *et al.* (2019), we define a lending observation as a credit line or term loan if it falls within one of the following categories: 364–day facility, revolver/line < 1 year, revolver/line $\geqslant 1$ year, revolver/term loan, term loan, and term loan A.

[3] Carey *et al.* (1998) and Ivashina (2009) demonstrate that this selection choice does not significantly affect the distribution of loans.

2.2. Measurement

Our approach to climate risk measurement is largely informed by the methodological framework developed by the Bank for International Settlements (2021), which involves scoring climate risk on the basis of accounting for portfolio and sectoral exposures. The measurement of climate risk comprises two major steps: We first create a state-level climate risk index (CRI_State), and then compute bank-level climate risk exposure (CRI_Bank) by weighting bank lending to a state by the climate risk index of the borrower's state (CRI_State).

The state-level climate risk index (CRI_State) quantifies the extent to which states have suffered direct loss associated with extreme weather events such as storms, floods, and heat waves. CRI_State is indicative of the severity of losses that a state suffers due to climate change, and is defined as the natural logarithm of the first principal component of six key climate risk indicators: (a) number of deaths, (b) number of deaths per 100,000 inhabitants, (c) sum of losses in USD at purchasing power parity (PPP), (d) losses per unit of Gross Domestic Product (GDP), (e) number of events, and (f) loss per event. A higher score for CRI_State corresponds to greater climate risk for state j in year t:

$$CRI\_State_{j,t} = pca(a_{j,t}, b_{j,t}, c_{j,t}, d_{j,t}, e_{j,t}, f_{j,t}). \tag{1}$$

The bank-level climate risk is the sum of a bank's lending share to an individual state weighted by the climate risk of the borrower's state, which can be expressed as follows:

$$CRI\_Bank_{i,t} = \sum \frac{L_{i,j,t}}{TL_{i,t}} CRI\_State_{j,t}, \tag{2}$$

where $L_{i,j,t}$ is the total outstanding loans made by bank i to borrowers in state j in year t. $TL_{i,t}$ is the total outstanding loans of bank i in year t. $\frac{L_{i,j,t}}{TL_{i,t}}$ measures a bank's lending share to a given state in a specific year. $CRI\_State_{j,t}$ is the climate risk index for state

j in year t as defined in Equation (1). For example, JP Morgan's lending share to Texas and Florida is 17% and 6% out of its total syndicated lending in 2016, respectively.

3. Empirical Design

3.1. Methodology

To examine the impact of bank-level climate risk on financial stability, we exploit the economic link between a lender bank and its borrower firms, and analyze how the exposure of a bank's borrowers to climate risk affects the bank's tail and systemic risk contribution. We specify our baseline model as follows:

$$Risk_{i,t} = \beta_0 + \beta_1 CRI\_Bank_{i,t-1} + \sum_{j=2}^{26} \beta_j Control_{i,t-1} + \text{FE} + \epsilon_{i,t}, \tag{3}$$

where $Risk_{i,t}$ is a set of variables of bank i at time t that is one of the following risk measures: TAIL5, TAIL1, Marginal Expected Shortfall (MES), Long-run Marginal Expected Shortfall (LRMES), ΔCoVaR5 and ΔCoVaR1. In detail, TAIL5 (TAIL1) is computed as expected shortfall (ES) at the 5% (1%) level:

$$ES_t^i = E[R_t^i | R_t^i \leqslant R_t^i(\alpha)], \tag{4}$$

where R_t^i denotes the daily stock return of bank i at time t. $R_t^i(\alpha)$ is the α quantile of bank returns. Setting α at 5% or 1%, ES measures the average return for a bank's stock during the 5% (1%) worst return days for the bank in a year.

Following Acharya *et al.* (2012), we compute MES as follows:

$$MES_t^i = E[R_t^i | R_t^m \leqslant q_\alpha], \tag{5}$$

where R_t^i is the same as previously defined; R_t^m represents the daily financial sector market return at time t; and q_α is the α quantile of market returns. Setting α=5%, MES measures the average bank equity return during the 5% worst return days for the banking industry in a year. MES quantifies the extent to which an individual bank's stock returns are low when market returns are low.

$LRMES$ is the long-run marginal expected shortfall (Acharya *et al.*, 2012) when the financial industry returns are below –2%, calculated as follows:

$$LRMES_t^i = 1 - exp(-18 \times (E[R_t^i | R_t^m < -2\%])). \tag{6}$$

We follow Adrian and Brunnermeier (2016) to estimate the time-varying $\Delta CoVaR$ for each bank at the 5% and 1% levels. Our estimation is based on quantile regressions using weekly data calculated using CRSP daily stock files for all financial institutions with two-digit Standard Industrial Classification (SIC) code between 60 and 67 inclusive.[4] We remove daily observations with missing or negative prices and retain banks with nonmissing stock return data on their ordinary common shares for a minimum of 260 weeks. We then merge the weekly stock data with quarterly balance sheet data from the CRSP/Compustat Merged dataset[5] and remove banks with book-to-market and leverage ratios that are less than zero or greater than 100.

$$X_t^i = \alpha^i + \gamma^i M_{t-1} + \epsilon_t^i, \tag{7}$$

$$X_t^{system} = \alpha^{system|i} + \beta^{system|i} X_t^i + \gamma^{system|i} M_{t-1} + \epsilon_t^{system|i}, \tag{8}$$

where X_t^i is the daily return on the market-valued total assets of bank i at time t; X_t^{system} is the daily return of the financial system, calculated as the market-value weighted average

[4] We adjust the changes in SIC code due to conversions of several large institutions into bank holding companies.

[5] Both equity return and balance sheet data are adjusted for mergers and acquisitions.

change in asset values for financial institutions. M_{t-1} is a set of state variables that include the change in the three-month Treasury bill rate, the change in the slope of the yield curve (i.e., the spread between the composite long-term bond yield and three-month Treasury bill rate), a short-term TED spread (i.e., the difference between the three-month LIBOR rate and the three-month Treasury bill rate), the change in credit spread between Moody's seasoned BAA corporate bond yield and the ten-year Treasury rate, the weekly market return computed from the S&P 500 index, the weekly real estate sector return in excess of the financial sector return, and equity volatility calculated as the 22–day rolling standard deviation of the daily CRSP stock market return.

From the estimation of equations (5) and (6) we obtain:

$$VaR_t^i(q) = \hat{\alpha}_q^i + \hat{\gamma}_q^i M_{t-1}, \tag{9}$$

$$CoVaR_t^i(q) = \hat{\alpha}_q^{system|i} + \hat{\beta}_q^{system|i} VaR_t^i(q) + \hat{\gamma}_q^{system|i} M_{t-1}, \tag{10}$$

where $\hat{\alpha}_q^i$, $\hat{\gamma}_q^i$, $\hat{\beta}_q^{system|i}$ and $\hat{\gamma}_q^{system|i}$ are coefficients obtained from quantile regressions at the 1% and 5% confidence levels. $\Delta CoVaR_t^i(q)$, which measures the marginal contribution of bank i to the risk of the system at time t, is computed as the difference between $CoVaR_t^i(q)$ conditional on the distress of the institution (i.e., q=5% or 1%) and $CoVaR_t^i(50\%)$ (i.e., the normal state of the institution):

$$\Delta CoVaR_t^i(q) = CoVaR_t^i(q) - CoVaR_t^i(50\%). \tag{11}$$

We obtain weekly $\Delta CoVaR_t^i(q)$ from the quantile regressions, and convert it to an annual frequency by first taking the mean of $\Delta CoVaR_t^i(q)$ and then applying a multiplier of 52 for each bank-year. We multiply TAIL5, TAIL1, MES, LRMES, and $\Delta CoVaR_t^i(q)$ by -1 such that higher values correspond to greater risk.

CRI_Bank is defined in Section 2.2. Our point of focus is the coefficient β_1. We control for a list of bank characteristics that are found to be relevant in explaining bank systemic risk (Brunnermeier *et al.*, 2020; Anginer *et al.*, 2018; Laeven *et al.*, 2016; Gauthier *et al.*, 2012). We include bank size (SIZE_Bank), equity ratio (EQRAT_Bank), market-to-book ratio (MTB_Bank), loans-to-assets ratio (LTA_Bank), loan loss provisioning (LLP_Bank), deposit ratio (DEPO_Bank), noninterest income ratio (NII_Bank), return on assets (ROA_Bank), operating expense management (OEM_Bank), and change in cost-to-income ratio (ΔCIR_Bank). Notably, since our *CRI_Bank* has an element of banking lending share, controlling for the book value of loans (LTA) thus allows us to gauge the incremental effect of syndicated lending in addition to bank loan books, on banks' tail risks, and systemic risk contribution.

We also control for a range of borrower firm characteristics that are relevant in explaining lending decisions and loan quality and to control for demand for credit, which include firm size (SIZE_Borrower), market-to-book ratio (MTB_Borrower), cash holding ratio (CASH_Borrower), current ratio (CURRENT_Borrower), interest coverage (COVER_Borrower), debt ratio (DEBT_Borrower), dividend payout (DPO_Borrower), profitability (EBITDA_Borrower), intangible assets ratio (INTAN_Borrower), fixed assets ratio (PPE_Borrower), and annual growth in sales revenue (ΔSALES_Borrower). We control for GDP and GDP growth (ΔGDP) for both lender and borrower states. Variable definitions are detailed in Appendix A. We also include year fixed effects in all regressions to account for economy-wide shocks on bank risk. We include bank fixed effects to control for unobservable time-invariant bank characteristics, and borrower firm fixed effects to control for latent constant characteristics of each borrowers and loan demand around loan origination. With this setup in place, variation in *CRI_Bank* explains the remaining variation. All continuous independent variables are winsorized at the 1^{st} and 99^{th} percentiles of their empirical distribution. Standard errors are adjusted for clustering at the bank-borrower lending relationship level.

3.2. Sample and Descriptive Statistics

We match borrower firms in the Dealscan database with annual financial statement information from Compustat using the linking table provided by Chava and Roberts (2008). We use data from the financial year prior to the year of loan origination to ensure that we use accounting information that is publicly available at the time of loan origination. Using the linking table provided by Schwert (2018), we merge lender banks active in Dealscan with financial statement data from Compustat. We exclude borrower firms that are located within the same state as the lender bank because our primary focus is the cross-state lending as a transmission channel for climate risk exposure, and inclusion of within-state lending would make it difficult to disentangle the impact of climate change on bank risks. We then aggregate all data at lender banks' and borrower firms' parent level to construct the "lender-borrower" sample. This sample contains information on 31 lender banks and 1,778 borrower firms between 1999 and 2017, forming a total of 7,830 lender-borrower-year observations. Table 1 reports sample composition. Panel A reports sample composition by year. Panel B reports sample composition by lender bank state. Panel C reports sample composition by borrower firm state.

[Table 1 about here.]

Table 2 presents descriptive statistics for all variables used in our analysis. For our key dependent variables, the average bank has tail risk at the 5% ($-$TAIL5) of 3.126%, tail risk at the 1% ($-$TAIL1) of 5.224%, marginal expected shortfall ($-$MES) of 3.623%, long-run marginal expected shortfall ($-$LRMES) of 0.483%, systemic risk contribution at the 5% level ($-\Delta$CoVaR5) of 0.834%, and systemic risk contribution at the 1% level ($-\Delta$CoVaR1) of 0.617%. For the key independent variable, the average value of CRI_Bank is 0.953, with a standard deviation of 10.038. CRI_Bank ranges from -14.893

to 29.634, with a higher value indicating greater climate risk. The average bank in our sample has log of total assets (SIZE_Bank) of 13.538 (mean total assets of $1.134 trillion), equity ratio (EQRAT_Bank) of 8.4%, market-to-book ratio (MTB_Bank) of 1.362, loans-to-assets ratio (LTA_Bank) of 44.2%, deposit ratio (DEPO_Bank) of 55.3%, noninterest income ratio (NII_Bank) of 2.5%, return on assets (ROA_Bank) of 0.9%, operating expense ratio (OEM_Bank) of 5.3%, and growth in cost-to-income ratio (ΔCIR_Bank) of −0.8%. These statistics suggest that the average bank tends to be very large, well-capitalized, and efficient although these averages may mask substantial cross-sectional and time-varying differences. Turning to the borrower controls, we find that the average borrower firm in our sample has a log of total assets (SIZE_Borrower) of 7.377 (mean total assets of $6,572 million), market-to-book ratio (MTB_Borrower) of 1.686, cash holding ratio (CASH_Borrower) of 8.1%, current ratio (CURRENT_Borrower) of 0.44, interest coverage (COVER_Borrower) of 24.172, debt ratio (DEBT_Borrower) of 29.2%, dividend payout ratio (DPO_Borrower) of 1.3%, profitability (EBITDA_Borrower) of 16.6%, intangible assets ratio (INTAN_Borrower) of 20.1%, fixed assets ratio (PPE_Borrower) of 33.4%, and growth in sales (ΔSALES_Borrower) of 14.7%. We also note that the average value of log GDP per capita is 10.871 and 10.812 for lender banks' and borrower firms' states, respectively, and average value of GDP growth (ΔGDP) is 1.315% and 1.285% for lender banks' and borrower firms' states, respectively.

[Table 2 about here.]

4. Results

Table 3 reports the baseline results from regressions of banks' tail and systemic risks on our climate risk measure and control variables. The variable of interest is CRI_Bank. We find that β_1, the coefficient for CRI_Bank, is statistically significant at the 10% level for ΔCoVaR5, at the 5% level for TAIL5 and TAIL1, and at the 1% level for MES, LRMES and ΔCoVaR1. For the purpose of interpretation, we normalize CRI_Bank so that β_1 captures the effect of a unit (one standard deviation) change in CRI_Bank on $Risk$. β_1 thus represents the percentage of additional $Risk$ generated, away from the mean $Risk$, associated with a one standard deviation increase in the pertinent CRI_Bank. A unit increase in CRI_Bank leads to an increase of 3.1% in TAIL5, 8.0% in TAIL1, 8.7% in MES, 2.5% in LRMES, 0.4% in ΔCoVaR5, and 0.9% in ΔCoVaR1. Overall, these results suggest that a higher level of climate risk acquired through the lending channel leads to greater banks' tail risks and their systemic risk contribution. Adjusted R^2 ranges from 90.7% to 96.7%, suggesting that a substantial proportion of the variation in the dependent variables are explained in the models identified.

[Table 3 about here.]

5. Robustness Tests

5.1. Instrumental Variables Approach

The instrumental variables (IV) approach is applicable to address endogeneity concerns arising from omitted variables, measurement errors and simultaneity. The IV approach successfully address endogeneity problems if the following conditions are satisfied: (1) the IV are correlated with endogenous regressors (relevance condition); (2) the IV are uncorrelated with the error term (exogeneity condition); and (3) the IV do not directly affect the dependent variable (exclusion condition). If conditions (2) and (3) are satisfied, the IV are valid. If condition (1) is satisfied but the correlations between the IVs and endogenous regressions are low, the IV are valid but weak.

The choices of IV are therefore important. We select two instruments: foreign loans as a percentage of total loans (FOREIGN) and population density (POP) of the borrower's state. These two instruments are suitable from both a theoretical and empirical perspective. A more stringent home-country climate policy is associated with an increase in banks' cross-border loan share as a means to practise regulatory arbitrage (Benincasa, 2021; Benincasa *et al.*, 2021). Albouy *et al.* (2016) find that population density is negatively correlated with climate risk such that climate risk has both a short- and long-term impact on individuals' cross-state mobility and migration preferences.

Table 4 reports results using the IV approach. CRI_Bank is found to have a positive and statistically significant impact on bank tail risks and systemic risk contribution across all model specifications. We perform postestimation tests including underidentification, weak identification, and overidentification tests. All six model specifications reject the under-identifying restrictions test: we reject the null hypothesis that the instruments are uncorrelated with the endogenous regressor at the 1% level. We also reject the null hypothesis of weak instruments at the 1% level, excluding instruments that are weakly correlated with the endogenous regressor. Thus, the instruments are not weak. Since we have two instruments and only one endogenous variable, we perform the Sargan-Hansen test of overidentifying restrictions: under the joint null hypothesis that the instruments are valid (i.e., uncorrelated with the error term, and that the excluded instruments are correctly excluded from the estimated equation), the test statistic follows a χ^2 distribution in the number of overidentifying restrictions. The test rejects the null hypothesis for overidentifying restrictions across all model specifications, which indicates that the instruments are overall valid. Hence, we conclude that the potential endogeneity problem does not bias our results.

[Table 4 about here.]

5.2. Alternative Climate Risk Measures

In this section, we describe our use of several alternative climate risk measures to check the robustness of our results to the choice of climate risk measures. We create three alternative climate risk measures: (1) an adjusted climate risk measure that accounts for borrowers' vulnerability to climate change; (2) a residual climate risk measure that is orthogonal to common risk factors; and (3) a climate risk measure calculated using the Germanwatch method.

5.2.1. Adjusted Climate Risk Measure

Climate risk events can inflict damage to physical assets, deprive firms of potential revenue, and disrupt normal operations and lead to operational losses (Huang *et al.*, 2017). Industries operating on nondeployed and long-lived capital assets are more vulnerable to damage to physical assets caused by extreme weather (Wilbanks *et al.*, 2007; McCarthy *et al.*, 2001). Moreover, industries that depend on moderate weather, with a reliance on both infrastructure and an extended supply chain, are likely to experience disruptions in operations due to extreme weather conditions (Challinor *et al.*, 2014; Wilbanks *et al.*, 2007). Huang *et al.* (2017) consider agriculture, energy (including mining and oil extraction), food products, healthcare, communications, business services, and transportation as vulnerable industries. We employ the industry classification developed by ING (2020) that accounts for the extremity in different industries' sensitivity to climate conditions and classifies industries into the three categories of high, medium, and low vulnerability to climate change (Appendix B). Industries such as coal, oil and gas, air and water transportation, and construction are considered as highly vulnerable to climate change.

The varying levels of borrower firms' vulnerability to climate change is expected to affect loan quality and credit risk exposure for lender banks differently. Therefore, we calibrate an adjusted climate risk index that accounts for borrower firms' vulnerability to climate change expressed as follows:

$$CRI\_Bank\_Adj_{i,t} = \sum \frac{L_{i,j,t} W \in \{1,2,3\}}{TL_{i,t}} CRI\_State_{j,t}, \tag{12}$$

where $L_{i,j,t}$, $TL_{i,t}$, and $CRI\_State_{j,t}$ are the same as defined in Equation (1) and (2). W is a re-weighting scheme that accounts for the borrower industry's vulnerability to climate change, as reported in Appendix B. W takes a value of 1, 2, and 3 when a borrower firm's industry presents low, medium, and high vulnerability to climate change, respectively.

Results based on the use of CRI_Bank_Adj are reported in Table 5. Compared to the baseline results reported in Table 3, both the effect size and statistical significance of the climate risk variable increase across all model specifications. These findings confirm that borrowers' vulnerability to climate change has an incremental impact on the positive association between climate risk channeled through lending, and banks' tail risks and systemic risk contribution.

[Table 5 about here.]

5.2.2. Residual Climate Risk Measure

Extreme weather events may systematically influence stock market performance (Lanfear *et al.*, 2019). In order to rule out the possibility that our climate risk measure captures predominantly or acts as a proxy for the systematic effect of climate risk events on the stock market, we create an alternative climate risk measure, CRI_Bank_Res, that is orthogonal to common risk factors identified in prior studies (Fabrizi *et al.*, 2021; Bessler *et al.*, 2015; Bessler and Kurmann, 2014), including interest rate risk, credit risk, commodity risk, foreign exchange risk, market risk, political risk, real estate risk, sovereign risk, and VIX Index. A detailed description of these common risk factors is reported in Appendix C. CRI_Bank_Res is computed as the residual from the regression of CRI_Bank on these common risk factors. We find consistent results based on CRI_Bank_Res and report them in Table 6.

[Table 6 about here.]

5.2.3. Germanwatch Method

Our main construct for the state-level climate risk employs a first principal component of six key climate risk indicators: (1) number of death, (2) number of deaths per 100,000 inhabitants, (3) sum of losses in USD at purchasing power parity (PPP), (4) losses per unit of Gross Domestic Product (GDP), (5) number of events, and (6) loss per event. To check the sensitivity of our results to the method to calibrating climate risk, we apply the Germanwatch method. Each state's climate risk index is the sum of the state's score in the first four indicating categories (i.e., indicators 1 to 4):

$$CRI\_State\_GW = \frac{1}{6} \times Death + \frac{1}{3} \times \frac{Death}{Population} + \frac{1}{6} \times Loss + \frac{1}{3} \times \frac{Loss}{GDP}. \quad (13)$$

We then calculate the bank-level climate risk exposure in the same way detailed in Section 2.2 but based on the above Germanwatch state-level climate risk index. Table 7 reports results based on this alternative climate risk measure. We find consistent results across all model specifications except for the coefficient of TAIL5 (Column 1) being not significant but preserving the correct sign.

[Table 7 about here.]

5.3. Interaction Tests

The climate risk measure used in our main analysis is the sum of weighted outstanding loans by climate risk index of borrowers' states. The fact that banks experience higher tail risks and make greater systemic risk contribution could be driven by lending regardless of the borrowers' exposure to climate risk. To take this into account, we check the robustness of our results to the way bank-level climate risk is constructed by performing analyses that include the bank-level climate risk in the decomposed form (i.e., weighted loan shares; state-level climate risk of the borrower's state) and include them as an interaction term. We first define a dummy variable, CRI_State_High, that takes a value of one if the climate risk index of the borrower's state is in the top quartile of its empirical distribution, and zero otherwise. We then interact CRI_State_High with the lending share of a bank to the specific state in a given year ($Loan\_Share$); the interaction term thus captures the difference in the impact on bank risks between loans issued to borrowers in high- and low-climate risk states. Table 8 reports a positive and statistically significant coefficient for the interaction term across all model specifications, which is consistent with the main inference that loans made to borrowers in states with higher climate risk are associated with larger lender banks' tail risks and systemic risk contribution.

[Table 8 about here.]

5.4. GARCH-$\Delta CoVaR$

Our main systemic risk measure, $\Delta CoVaR$, is computed using the quantile estimation procedure detailed in Section 3. One potential shortcoming of this approach is that it models time-varying moments merely as a function of aggregate state variables (Adrian and Brunnermeier, 2016). We use the bivariate diagonal GARCH model as an alternative method to calculate the time-varying covariance between banks and the financial system, which explicitly captures the dynamic evolution of systemic risk contributions. Table 9 reports regression results based on GARCH-$\Delta CoVaR$, which is consistent with the baseline results. However, the sample size is relatively smaller than the one for the baseline test because the GARCH estimation does not converge for all banks. Our baseline results do not appear to be dependent on the estimation method used to compute $\Delta CoVaR$.

[Table 9 about here.]

5.5. *Weighted Least Squares*

Panel B of Table 1 indicates a substantial variation in the number observations across states where lender banks are headquartered. For this reason, we use state-weighted least squares estimation to control for the different weights of lender bank states in the sample. State Population is used as the weight. Results for this specification tests are reported in Panel A of Table 10. We further employ a capitalization-weighted least squares specification to account for possible greater contributions to systemic risk by larger banks. Laeven *et al.* (2016) find that larger banks have significantly higher systemic risk contributions. The weight is computed as a bank's end-of-year market capitalization divided by the total capitalization of the financial industry at the same point in time. We report results for this specification in Panel B of Table 10. Overall, results using the weighted least squares estimation provide further support for the baseline findings.

[Table 10 about here.]

5.6. *Standard Errors*

We perform two additional tests to check the robustness of our results to the method standard errors are computed. First, we cluster standard errors at borrowers' state level and obtain similar results as reported in Panel A of Table 11, with only TAIL1 being an exception. Second, we follow Newey and West (1987) to compute heteroskedasticity- and autocorrelation-consistent (HAC) standard errors that allow for up to two periods of autocorrelation, and report results in Panel B of Table 11. Overall, these results confirm that our main results are robust to different methods of calculating standard errors.

[Table 11 about here.]

6. Conclusions

This paper provides evidence that more climate risk exposure acquired through the lending channel is associated with greater banks' tail risks and systemic risk contribution. This effect is both statistically and economically significant: An increase by one standard deviation in the bank-level climate risk measure leads to an increase of 3.1% in tail risk at 5%, 8.0% in tail risk at 1%, 8.7% in the marginal expected shortfall, 2.5% in the long-run marginal expected shortfall, 0.4% in systemic risk contribution at 5%, and 0.9% in systemic risk contribution at 1%. Our analysis starts with crafting a bank-level climate risk measure using the NOAA Billion-Dollar Weather and Climate Disasters data and Dealscan syndicated lending data, followed by tests of the impact of banks' climate risk exposure on their tail risks and systemic risk contribution based on a sample of 7,830 lender-borrower-year observations comprised of 31 lender banks and 1,778 borrower firms for the period of 1999–2017. To alleviate endogeneity concerns, we employ an instrumental variables approach that avails of an exogenous source of variation in bank-level climate risk. Our results are robust to several alternative climate risk measures, including an adjusted climate risk measure accounting for borrowers' vulnerability to climate change, a residual climate risk measure that is orthogonal to common risk factors, and an alternative climate risk measure computed following the Germanwatch method. Our results also hold with interaction tests that decompose the climate risk measure, an alternative method to estimate systemic risk, weighted least squares estimators, and alternative methods to compute standard errors.

This paper addresses a recent call for developing methodologies that facilitate a successful assessment of the risks that climate change poses to financial stability (Battiston *et al.*, 2021), and provides validation on central banks' involvement in safeguarding monetary and financial stability against climate risk. We focus on the impact of physical climate risk on bank tail risks and systemic risk contribution, while remaining silent on the effects of transition climate risk. We acknowledge that the latter represents an interesting avenue for future research. Future work could, for instance, attempt to draw the dynamics of the interaction between physical and transition climate risks, and its outcomes at various levels. The major challenge in this respect is designing an identification strategy addressing the feedback effect between climate risk events and climate risk policy. Another aspect that is not considered in our setting is the effect of bank interconnectedness on climate risk transmission, which presents another opportunity for future research to explore: how do banks' climate risks transmit through a network of interconnectedness?

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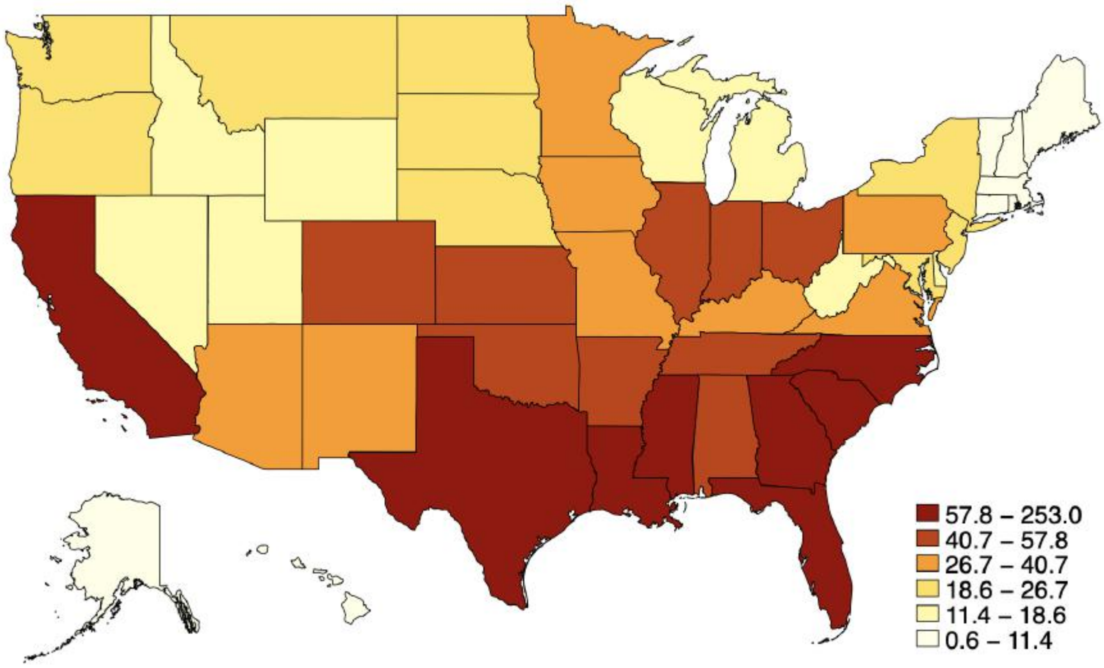

Figure 1: Cumulative Losses (USD bn) of Climate Risk Events 1980–2020

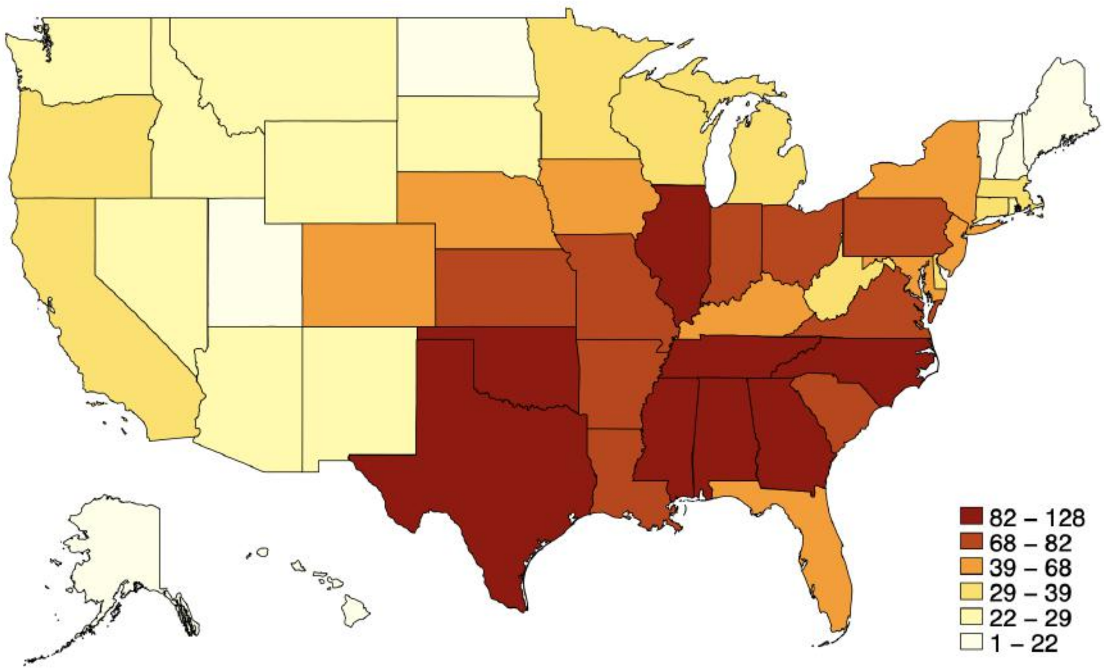

Figure 2: Cumulative Frequency of Climate Risk Events 1980–2020

Table 1: Sample Composition

This table reports the sample composition. Panel A reports the sample composition by year. Panel B reports the sample composition by lender bank state. Panel C reports the sample composition by borrower firm state.

Panel A. Sample Composition by Year

Year	Frequency	Percent	Cumulative
1999	379	4.84	4.84
2000	432	5.52	10.36
2001	491	6.27	16.63
2002	472	6.03	22.66
2003	526	6.72	29.37
2004	579	7.39	36.77
2005	589	7.52	44.29
2006	489	6.25	50.54
2007	444	5.67	56.21
2008	271	3.46	59.67
2009	246	3.14	62.81
2010	376	4.80	67.61
2011	585	7.47	75.08
2012	421	5.38	80.46
2013	408	5.21	85.67
2014	406	5.19	90.86
2015	350	4.47	95.33
2016	305	3.90	99.22
2017	61	0.78	100.00
Total	7,830	100.00	

Panel B. Sample Composition by Lender State

State	Frequency	Percent	Cumulative
Alabama	29	0.37	0.37
California	955	12.20	12.57
Georgia	217	2.77	15.34
Illinois	276	3.52	18.86
Louisiana	8	0.10	18.97
Massachusetts	191	2.44	21.40
Minnesota	156	1.99	23.40
New Jersey	3	0.04	23.44
New York	2,646	33.79	57.23
North Carolina	2,859	36.51	93.74
Ohio	186	2.38	96.12
Pennsylvania	251	3.21	99.32
Rhode Island	10	0.13	99.45
Texas	36	0.46	99.91
Utah	5	0.06	99.97
Wisconsin	2	0.03	100.00
Total	7,830	100.00	

Panel C. Sample Composition by Borrower State

State	Frequency	Percent	Cumulative
Alabama	33	0.42	0.42
Alaska	3	0.04	0.46
Arizona	161	2.06	2.52
Arkansas	76	0.97	3.49
California	509	6.50	9.99
Colorado	263	3.36	13.35
Connecticut	183	2.34	15.68
Delaware	13	0.17	15.85
Florida	390	4.98	20.83
Georgia	284	3.63	24.46
Hawaii	9	0.11	24.57
Idaho	26	0.33	24.90
Illinois	495	6.32	31.23
Indiana	132	1.69	32.91
Iowa	17	0.22	33.13
Kansas	45	0.57	33.70
Kentucky	83	1.06	34.76
Louisiana	85	1.09	35.85
Maine	12	0.15	36.00
Maryland	99	1.26	37.27
Massachusetts	247	3.15	40.42
Michigan	190	2.43	42.85
Minnesota	212	2.71	45.56
Mississippi	3	0.04	45.59
Missouri	225	2.87	48.47
Nebraska	29	0.37	48.84
Nevada	81	1.03	49.87
New Hampshire	20	0.26	50.13
New Jersey	310	3.96	54.09
New Mexico	14	0.18	54.27
New York	204	2.61	56.87
North Carolina	125	1.60	58.47
North Dakota	21	0.27	58.74
Ohio	383	4.89	63.63
Oklahoma	85	1.09	64.71
Oregon	102	1.30	66.02
Pennsylvania	291	3.72	69.73
Rhode Island	46	0.59	70.32
South Carolina	53	0.68	71.00
South Dakota	9	0.11	71.11
Tennessee	185	2.36	73.47
Texas	1,374	17.55	91.02
Utah	48	0.61	91.63
Vermont	10	0.13	91.76
Virginia	260	3.32	95.08
Washington	143	1.83	96.91
West Virginia	14	0.18	97.09
Wisconsin	228	2.91	100.00
Total	7,830	100.00	

Table 2: Descriptive Statistics

This table presents descriptive statistics of the variables studied. N refers to the number of observations. S.D. is the standard deviation. Min and Max refer to the minimum and maximum values, respectively. Variables are defined in Appendix A.

	N	Mean	S.D.	Min	Median	Max
−TAIL5	7,830	3.126	1.911	0.969	2.712	14.354
−TAIL1	7,830	5.224	3.913	1.551	4.328	27.258
−MES	7,830	3.623	2.637	0.567	3.068	14.284
−LRMES	7,830	0.483	0.185	0.100	0.480	0.973
−ΔCoVaR5	7,830	0.834	0.296	0.256	0.775	2.284
−ΔCoVaR1	7,830	0.617	0.331	0.167	0.601	2.675
CRI_Bank	7,830	0.953	10.038	-14.893	-0.849	29.634
SIZE_Bank	7,830	13.538	1.086	8.404	13.920	14.728
EQRAT_Bank	7,830	0.084	0.014	0.040	0.083	0.118
MTB_Bank	7,830	1.362	0.533	0.259	1.339	2.940
LTA_Bank	7,830	0.442	0.120	0.121	0.440	0.740
LLP_Bank	7,830	0.005	0.005	0.000	0.004	0.022
DEPO_Bank	7,830	0.553	0.094	0.247	0.552	0.864
NII_Bank	7,830	0.025	0.006	0.010	0.024	0.050
ROA_Bank	7,830	0.009	0.005	-0.006	0.010	0.019
OEM_Bank	7,830	0.053	0.015	0.028	0.054	0.134
ΔCIR_Bank	7,830	-0.008	0.096	-0.192	-0.016	0.246
GDP_Bank	7,830	10.871	0.147	10.647	10.845	11.155
ΔGDP_Bank	7,830	1.315	2.022	-5.546	1.454	5.207
SIZE_Borrower	7,830	7.337	1.662	2.015	7.312	10.929
MTB_Borrower	7,830	1.686	0.868	0.690	1.422	6.305
CASH_Borrower	7,830	0.081	0.100	0.000	0.042	0.598
CURRENT_Borrower	7,830	0.441	0.395	0.000	0.339	2.617
COVER_Borrower	7,830	24.172	60.542	-28.588	7.660	429.051
DEBT_Borrower	7,830	0.292	0.190	0.000	0.278	1.111
DPO_Borrower	7,830	0.013	0.022	0.000	0.003	0.173
EBITDA_Borrower	7,830	0.166	0.153	-0.697	0.137	0.683
INTAN_Borrower	7,830	0.201	0.198	0.000	0.139	0.750
PPE_Borrower	7,830	0.334	0.249	0.010	0.263	0.911
ΔSALES_Borrower	7,830	0.147	0.432	-0.699	0.076	4.956
GDP_Borrower	7,830	10.812	0.134	10.476	10.809	11.131
ΔGDP_Borrower	7,830	1.285	2.164	-5.463	1.407	6.020

Table 3: Baseline Results

This table reports test results of the impact of the banks' climate risk exposure on their tail and systemic risks. The regressions include bank, borrower and year fixed effects (not reported). Standard errors are adjusted for clustering at the bank-borrower (lending relationship) level. ***, ** and * indicate statistical significance at the 1%, 5%, and 10% levels, respectively. Robust t-statistics are reported in parentheses. Variables are defined in Appendix A.

	(1) −TAIL5	(2) −TAIL1	(3) −MES	(4) −LRMES	(5) −ΔCoVaR5	(6) −ΔCoVaR1
CRI_Bank	0.031**	0.080**	0.087***	0.025***	0.004*	0.009***
	(2.077)	(2.152)	(4.547)	(15.156)	(1.859)	(2.744)
SIZE_Bank	-0.610***	-1.259***	-0.621***	-0.024**	-0.035***	0.094***
	(-6.454)	(-4.658)	(-4.383)	(-2.355)	(-2.609)	(5.501)
EQRAT_Bank	-13.531***	-6.218	-7.716***	-1.004***	1.461***	2.482***
	(-7.469)	(-1.478)	(-3.018)	(-4.178)	(8.201)	(9.136)
MTB_Bank	-0.753***	-1.763***	-0.661***	-0.040***	-0.020***	0.035***
	(-9.311)	(-8.266)	(-6.838)	(-5.231)	(-2.752)	(3.028)
LTA_Bank	0.583*	-1.680**	1.515***	0.010	0.316***	0.424***
	(1.741)	(-2.151)	(4.061)	(0.335)	(8.266)	(7.752)
LLP_Bank	5.293	120.632***	38.338***	7.157***	3.411***	-6.372***
	(0.561)	(6.269)	(3.491)	(7.383)	(3.380)	(-3.906)
DEPO_Bank	-1.760***	-2.806***	-1.733***	-0.093***	-0.062	0.057
	(-4.580)	(-2.704)	(-3.695)	(-2.909)	(-1.386)	(0.884)
NII_Bank	30.917***	9.567	60.605***	3.200***	4.444***	7.083***
	(5.853)	(0.836)	(9.637)	(6.610)	(8.794)	(9.274)
ROA_Bank	-67.935***	-49.993***	-107.255***	-5.330***	-5.181***	-10.009***
	(-8.777)	(-2.929)	(-11.679)	(-8.638)	(-7.529)	(-9.076)
OEM_Bank	7.071*	28.508***	-24.250***	-1.344***	-2.923***	-3.885***
	(1.709)	(2.937)	(-5.245)	(-4.847)	(-8.626)	(-6.138)
ΔCIR_Bank	-0.230	-0.458	-0.833***	-0.051***	0.023	0.082***
	(-1.582)	(-1.324)	(-4.438)	(-4.072)	(1.461)	(2.623)
GDP_Bank	5.040***	11.439***	6.702***	-0.202***	0.739***	0.448***
	(7.656)	(7.302)	(7.825)	(-3.169)	(10.515)	(4.549)
ΔGDP_Bank	0.064***	0.041**	-0.000	-0.003***	-0.006***	-0.010***
	(8.233)	(2.164)	(-0.046)	(-4.068)	(-8.257)	(-8.789)
SIZE_Borrower	0.005	-0.052	-0.017	-0.003*	-0.001	-0.004
	(0.298)	(-1.142)	(-0.764)	(-1.938)	(-0.357)	(-1.215)
MTB_Borrower	-0.015	-0.066*	-0.037**	-0.002**	-0.000	-0.003
	(-1.117)	(-1.911)	(-2.071)	(-1.988)	(-0.231)	(-1.359)
CASH_Borrower	0.030	0.354	0.313	0.021*	0.006	-0.010
	(0.190)	(0.881)	(1.535)	(1.751)	(0.370)	(-0.413)
CURRENT_Borrower	-0.001	-0.003	0.003	0.000	-0.001	-0.001
	(-0.036)	(-0.048)	(0.119)	(0.045)	(-0.406)	(-0.265)
COVER_Borrower	0.000***	0.001	0.000*	0.000	0.000	0.000
	(2.635)	(1.232)	(1.676)	(0.717)	(0.306)	(0.244)
DEBT_Borrower	-0.086	-0.344**	-0.076	0.000	-0.003	-0.001
	(-1.485)	(-2.149)	(-1.012)	(0.014)	(-0.352)	(-0.069)
DPO_Borrower	-0.246	0.462	-0.149	0.037	-0.077	-0.089
	(-0.558)	(0.358)	(-0.219)	(0.808)	(-1.395)	(-1.006)
EBITDA_Borrower	-0.269**	-0.549*	-0.287**	-0.006	-0.016	-0.032*
	(-2.357)	(-1.808)	(-2.074)	(-0.841)	(-1.533)	(-1.744)
INTAN_Borrower	0.068	0.226	0.177	0.020**	0.005	0.005
	(0.587)	(0.788)	(1.276)	(2.077)	(0.366)	(0.264)
PPE_Borrower	0.012	-0.003	0.141	0.016	-0.003	-0.003
	(0.078)	(-0.008)	(0.786)	(1.391)	(-0.177)	(-0.116)
ΔSALES_Borrower	0.018	0.056	0.047**	0.001	0.002	0.001
	(1.076)	(1.350)	(2.216)	(0.563)	(0.841)	(0.302)
GDP_Borrower	-0.012	0.468	-0.128	-0.038**	-0.005	-0.009
	(-0.055)	(0.844)	(-0.535)	(-2.234)	(-0.196)	(-0.215)
ΔGDP_Borrower	0.008*	0.013	0.012**	0.000	0.000	-0.000
	(1.695)	(0.987)	(2.017)	(0.729)	(0.068)	(-0.297)
Constant	-41.018***	-103.337***	-56.918***	3.626***	-6.773***	-5.699***
	(-5.909)	(-6.312)	(-6.436)	(5.663)	(-9.410)	(-5.255)
Bank FE	Yes	Yes	Yes	Yes	Yes	Yes
Borrower FE	Yes	Yes	Yes	Yes	Yes	Yes
Year FE	Yes	Yes	Yes	Yes	Yes	Yes
Observations	7,830	7,830	7,830	7,830	7,830	7,830
Adjusted R^2	0.945	0.907	0.953	0.953	0.967	0.938

Table 4: Instrumental Variables Approach Results

This table reports instrumental variables two-stage least squares regression results of the impact of the banks' climate risk exposure on their tail and systemic risks. The regressions include bank, borrower and year fixed effects (not reported). Standard errors are adjusted for clustering at the bank-borrower (lending relationship) level. ***, ** and * indicate statistical significance at the 1%, 5%, and 10% levels, respectively. Robust t-statistics are reported in parentheses. Variables are defined in Appendix A.

	(1) −TAIL5	(2) −TAIL1	(3) −MES	(4) −LRMES	(5) −ΔCoVaR5	(6) −ΔCoVaR1
CRI_Bank	2.891***	4.324***	2.397***	0.135***	0.067**	0.589***
	(4.550)	(4.027)	(4.265)	(4.394)	(2.184)	(4.666)
SIZE_Bank	-2.897***	-4.652***	-2.468***	-0.112***	-0.086***	-0.826***
	(-5.429)	(-5.160)	(-5.228)	(-4.347)	(-3.319)	(-4.762)
EQRAT_Bank	-18.658***	-13.826**	-11.856***	-1.201***	1.347***	3.540***
	(-5.351)	(-2.346)	(-3.844)	(-7.128)	(7.974)	(4.760)
MTB_Bank	-1.528***	-2.913***	-1.286***	-0.070***	-0.038***	-0.177***
	(-7.163)	(-8.083)	(-6.818)	(-6.761)	(-3.646)	(-3.190)
LTA_Bank	2.895***	1.750	3.382***	0.098***	0.368***	-0.085
	(3.807)	(1.362)	(5.026)	(2.671)	(9.981)	(-0.553)
LLP_Bank	82.138***	234.644***	100.395***	10.102***	5.121***	-28.318***
	(3.666)	(6.198)	(5.066)	(9.332)	(4.719)	(-6.862)
DEPO_Bank	-9.516***	-14.313***	-7.996***	-0.390***	-0.235***	-0.843***
	(-5.140)	(-4.576)	(-4.883)	(-4.361)	(-2.621)	(-2.932)
NII_Bank	28.143***	5.451	58.364***	3.094***	4.383***	15.726***
	(3.430)	(0.393)	(8.041)	(7.804)	(11.026)	(7.702)
ROA_Bank	-6.901	40.561	-57.967***	-2.991***	-3.823***	-21.512***
	(-0.381)	(1.324)	(-3.615)	(-3.415)	(-4.354)	(-7.661)
OEM_Bank	-41.025***	-42.851**	-63.091***	-3.187***	-3.993***	-18.673***
	(-3.306)	(-2.044)	(-5.748)	(-5.315)	(-6.643)	(-7.059)
ΔCIR_Bank	4.108***	5.979***	2.670***	0.115**	0.120**	0.761***
	(4.085)	(3.518)	(3.002)	(2.373)	(2.460)	(4.032)
GDP_Bank	3.401***	9.007***	5.378***	-0.264***	0.702***	3.153***
	(3.069)	(4.811)	(5.488)	(-4.940)	(13.085)	(8.436)
ΔGDP_Bank	0.146***	0.163***	0.066***	-0.000	-0.004***	-0.011***
	(6.217)	(4.114)	(3.178)	(-0.280)	(-3.594)	(-2.882)
SIZE_Borrower	0.020	-0.030	-0.005	-0.002	-0.000	-0.007
	(0.452)	(-0.410)	(-0.133)	(-1.140)	(-0.206)	(-0.924)
MTB_Borrower	0.012	-0.026	-0.015	-0.001	0.000	-0.006
	(0.374)	(-0.472)	(-0.530)	(-0.893)	(0.170)	(-1.085)
CASH_Borrower	0.638*	1.256**	0.804***	0.045***	0.019	0.019
	(1.813)	(2.114)	(2.584)	(2.633)	(1.142)	(0.314)
CURRENT_Borrower	-0.056	-0.084	-0.041	-0.002	-0.003	-0.008
	(-0.982)	(-0.877)	(-0.818)	(-0.733)	(-0.915)	(-0.824)
COVER_Borrower	0.001	0.001	0.000	0.000	0.000	-0.000
	(1.356)	(1.173)	(1.397)	(0.794)	(0.495)	(-0.272)
DEBT_Borrower	-0.176	-0.477*	-0.148	-0.003	-0.005	-0.017
	(-1.136)	(-1.822)	(-1.083)	(-0.449)	(-0.606)	(-0.630)
DPO_Borrower	-2.684**	-3.156	-2.118*	-0.057	-0.131**	-0.446**
	(-2.101)	(-1.462)	(-1.874)	(-0.918)	(-2.113)	(-2.002)
EBITDA_Borrower	-0.365*	-0.692**	-0.364**	-0.010	-0.018*	-0.021
	(-1.870)	(-2.096)	(-2.106)	(-1.049)	(-1.910)	(-0.606)
INTAN_Borrower	0.485*	0.846*	0.514**	0.036***	0.014	0.017
	(1.809)	(1.865)	(2.167)	(2.772)	(1.067)	(0.367)
PPE_Borrower	0.480	0.693	0.520*	0.034**	0.008	0.027
	(1.466)	(1.251)	(1.792)	(2.176)	(0.486)	(0.470)
ΔSALES_Borrower	-0.014	0.009	0.021	-0.000	0.001	-0.004
	(-0.315)	(0.125)	(0.553)	(-0.115)	(0.581)	(-0.497)
GDP_Borrower	-0.282	0.068	-0.346	-0.048*	-0.011	-0.049
	(-0.514)	(0.073)	(-0.714)	(-1.823)	(-0.428)	(-0.503)
ΔGDP_Borrower	0.012	0.018	0.015	0.000	0.000	-0.000
	(1.063)	(0.977)	(1.534)	(0.844)	(0.212)	(-0.174)
Bank FE	Yes	Yes	Yes	Yes	Yes	Yes
Borrower FE	Yes	Yes	Yes	Yes	Yes	Yes
Year FE	Yes	Yes	Yes	Yes	Yes	Yes
Underidentification (P-value)	0.000	0.000	0.000	0.000	0.000	0.000
Weak identification (F-statistic)	11.751***	11.751***	11.751***	11.751***	11.751***	11.751***
Overidentification (P-value)	0.843	0.681	0.733	0.252	0.230	0.303
Observations	7,830	7,830	7,830	7,830	7,830	7,830

Table 5: Alternative Climate Risk Measure: Adjusting for Borrowers' Vulnerability to Climate Change

This table reports test results of the impact of the banks' climate risk exposure on their tail and systemic risks based on the use of an alternative climate risk measure adjusting for borrowers' vulnerability to climate change. The regressions include bank, borrower and year fixed effects (not reported). Standard errors are adjusted for clustering at the bank-borrower (lending relationship) level. ***, ** and * indicate statistical significance at the 1%, 5%, and 10% levels, respectively. Robust t-statistics are reported in parentheses. Variables are defined in Appendix A.

	(1)	(2)	(3)	(4)	(5)	(6)
	−TAIL5	−TAIL1	−MES	−LRMES	−ΔCoVaR5	−ΔCoVaR1
CRI_Bank_Adj	0.064***	0.122***	0.112***	0.025***	0.006***	0.012***
	(4.076)	(3.143)	(5.576)	(15.451)	(2.919)	(3.512)
SIZE_Bank	-0.634***	-1.289***	-0.637***	-0.023**	-0.036***	0.092***
	(-6.687)	(-4.761)	(-4.480)	(-2.233)	(-2.715)	(5.378)
EQRAT_Bank	-13.702***	-6.507	-7.955***	-1.046***	1.447***	2.455***
	(-7.535)	(-1.544)	(-3.106)	(-4.307)	(8.128)	(9.046)
MTB_Bank	-0.764***	-1.780***	-0.672***	-0.041***	-0.021***	0.034***
	(-9.409)	(-8.311)	(-6.918)	(-5.289)	(-2.844)	(2.895)
LTA_Bank	0.598*	-1.668**	1.514***	0.005	0.317***	0.424***
	(1.795)	(-2.142)	(4.064)	(0.160)	(8.271)	(7.756)
LLP_Bank	6.737	122.829***	39.976***	7.353***	3.519***	-6.185***
	(0.710)	(6.385)	(3.633)	(7.521)	(3.484)	(-3.778)
DEPO_Bank	-1.857***	-2.935***	-1.813***	-0.094***	-0.069	0.047
	(-4.845)	(-2.828)	(-3.863)	(-2.946)	(-1.519)	(0.730)
NII_Bank	30.547***	8.879	59.989***	3.071***	4.412***	7.015***
	(5.795)	(0.774)	(9.575)	(6.365)	(8.724)	(9.166)
ROA_Bank	-66.604***	-47.896***	-105.633***	-5.104***	-5.079***	-9.825***
	(-8.602)	(-2.797)	(-11.513)	(-8.219)	(-7.372)	(-8.867)
OEM_Bank	6.430	27.634***	-24.816***	-1.366***	-2.967***	-3.952***
	(1.544)	(2.832)	(-5.326)	(-4.913)	(-8.763)	(-6.218)
ΔCIR_Bank	-0.166	-0.366	-0.771***	-0.046***	0.028*	0.090***
	(-1.114)	(-1.034)	(-4.003)	(-3.651)	(1.724)	(2.809)
GDP_Bank	4.940***	11.259***	6.546***	-0.233***	0.730***	0.431***
	(7.475)	(7.141)	(7.645)	(-3.644)	(10.352)	(4.347)
ΔGDP_Bank	0.065***	0.043**	0.001	-0.003***	-0.006***	-0.010***
	(8.359)	(2.273)	(0.113)	(-3.823)	(-8.084)	(-8.562)
SIZE_Borrower	0.006	-0.051	-0.016	-0.003*	-0.001	-0.004
	(0.318)	(-1.131)	(-0.746)	(-1.894)	(-0.345)	(-1.198)
MTB_Borrower	-0.015	-0.066*	-0.037**	-0.002**	-0.000	-0.003
	(-1.101)	(-1.906)	(-2.069)	(-2.007)	(-0.221)	(-1.352)
CASH_Borrower	0.038	0.364	0.319	0.021*	0.006	-0.009
	(0.238)	(0.906)	(1.567)	(1.750)	(0.401)	(-0.384)
CURRENT_Borrower	-0.001	-0.004	0.003	0.000	-0.001	-0.001
	(-0.064)	(-0.062)	(0.101)	(0.050)	(-0.419)	(-0.277)
COVER_Borrower	0.000***	0.001	0.000*	0.000	0.000	0.000
	(2.662)	(1.249)	(1.703)	(0.777)	(0.321)	(0.266)
DEBT_Borrower	-0.088	-0.346**	-0.077	0.000	-0.003	-0.001
	(-1.508)	(-2.161)	(-1.027)	(0.008)	(-0.363)	(-0.079)
DPO_Borrower	-0.269	0.436	-0.162	0.039	-0.078	-0.090
	(-0.609)	(0.337)	(-0.237)	(0.865)	(-1.422)	(-1.025)
EBITDA_Borrower	-0.269**	-0.549*	-0.285**	-0.006	-0.016	-0.031*
	(-2.347)	(-1.802)	(-2.061)	(-0.773)	(-1.528)	(-1.738)
INTAN_Borrower	0.073	0.232	0.181	0.020**	0.005	0.005
	(0.630)	(0.809)	(1.302)	(2.059)	(0.389)	(0.286)
PPE_Borrower	0.017	0.003	0.144	0.016	-0.002	-0.002
	(0.113)	(0.009)	(0.806)	(1.372)	(-0.156)	(-0.098)
ΔSALES_Borrower	0.017	0.055	0.046**	0.001	0.002	0.001
	(1.044)	(1.328)	(2.186)	(0.517)	(0.823)	(0.281)
GDP_Borrower	-0.012	0.471	-0.125	-0.037**	-0.005	-0.008
	(-0.055)	(0.851)	(-0.523)	(-2.168)	(-0.192)	(-0.207)
ΔGDP_Borrower	0.008*	0.013	0.012**	0.000	0.000	-0.000
	(1.688)	(0.980)	(2.000)	(0.657)	(0.059)	(-0.311)
Constant	-39.505***	-100.868***	-54.939***	3.938***	-6.654***	-5.477***
	(-5.657)	(-6.104)	(-6.189)	(6.112)	(-9.181)	(-4.984)
Bank FE	Yes	Yes	Yes	Yes	Yes	Yes
Borrower FE	Yes	Yes	Yes	Yes	Yes	Yes
Year FE	Yes	Yes	Yes	Yes	Yes	Yes
Observations	7,830	7,830	7,830	7,830	7,830	7,830
Adjusted R^2	0.945	0.907	0.953	0.953	0.967	0.938

Table 6: Alternative Climate Risk Measure: Residual Climate Risk

This table reports test results of the impact of the banks' climate risk exposure on their tail and systemic risks based on the use of an alternative climate risk measure computed as a residual of common risk factors. The regressions include bank, borrower and year fixed effects (not reported). Standard errors are adjusted for clustering at the bank-borrower (lending relationship) level. ***, ** and * indicate statistical significance at the 1%, 5%, and 10% levels, respectively. Robust t-statistics are reported in parentheses. Variables are defined in Appendix A.

	(1) −TAIL5	(2) −TAIL1	(3) −MES	(4) −LRMES	(5) −ΔCoVaR5	(6) −ΔCoVaR1
CRI_Bank_Res	0.015**	0.040**	0.043***	0.013***	0.002*	0.005***
	(2.077)	(2.152)	(4.547)	(15.156)	(1.859)	(2.744)
SIZE_Bank	-0.610***	-1.259***	-0.621***	-0.024**	-0.035***	0.094***
	(-6.454)	(-4.658)	(-4.383)	(-2.355)	(-2.609)	(5.501)
EQRAT_Bank	-13.531***	-6.218	-7.716***	-1.004***	1.461***	2.482***
	(-7.469)	(-1.478)	(-3.018)	(-4.178)	(8.201)	(9.136)
MTB_Bank	-0.753***	-1.763***	-0.661***	-0.040***	-0.020***	0.035***
	(-9.311)	(-8.266)	(-6.838)	(-5.231)	(-2.752)	(3.028)
LTA_Bank	0.583*	-1.680**	1.515***	0.010	0.316***	0.424***
	(1.741)	(-2.151)	(4.061)	(0.335)	(8.266)	(7.752)
LLP_Bank	5.293	120.632***	38.338***	7.157***	3.411***	-6.372***
	(0.561)	(6.269)	(3.491)	(7.383)	(3.380)	(-3.906)
DEPO_Bank	-1.760***	-2.806***	-1.733***	-0.093***	-0.062	0.057
	(-4.580)	(-2.704)	(-3.695)	(-2.909)	(-1.386)	(0.884)
NII_Bank	30.917***	9.567	60.605***	3.200***	4.444***	7.083***
	(5.853)	(0.836)	(9.637)	(6.610)	(8.794)	(9.274)
ROA_Bank	-67.935***	-49.993***	-107.255***	-5.330***	-5.181***	-10.009***
	(-8.777)	(-2.929)	(-11.679)	(-8.638)	(-7.529)	(-9.076)
OEM_Bank	7.071*	28.508***	-24.250***	-1.344***	-2.923***	-3.885***
	(1.709)	(2.937)	(-5.245)	(-4.847)	(-8.626)	(-6.138)
ΔCIR_Bank	-0.230	-0.458	-0.833***	-0.051***	0.023	0.082***
	(-1.582)	(-1.324)	(-4.438)	(-4.072)	(1.461)	(2.623)
GDP_Bank	5.040***	11.439***	6.702***	-0.202***	0.739***	0.448***
	(7.656)	(7.302)	(7.825)	(-3.169)	(10.515)	(4.549)
ΔGDP_Bank	0.064***	0.041**	-0.000	-0.003***	-0.006***	-0.010***
	(8.233)	(2.164)	(-0.046)	(-4.068)	(-8.257)	(-8.789)
SIZE_Borrower	0.005	-0.052	-0.017	-0.003*	-0.001	-0.004
	(0.298)	(-1.142)	(-0.764)	(-1.938)	(-0.357)	(-1.215)
MTB_Borrower	-0.015	-0.066*	-0.037**	-0.002**	-0.000	-0.003
	(-1.117)	(-1.911)	(-2.071)	(-1.988)	(-0.231)	(-1.359)
CASH_Borrower	0.030	0.354	0.313	0.021*	0.006	-0.010
	(0.190)	(0.881)	(1.535)	(1.751)	(0.370)	(-0.413)
CURRENT_Borrower	-0.001	-0.003	0.003	0.000	-0.001	-0.001
	(-0.036)	(-0.048)	(0.119)	(0.045)	(-0.406)	(-0.265)
COVER_Borrower	0.000***	0.001	0.000*	0.000	0.000	0.000
	(2.635)	(1.232)	(1.676)	(0.717)	(0.306)	(0.244)
DEBT_Borrower	-0.086	-0.344**	-0.076	0.000	-0.003	-0.001
	(-1.485)	(-2.149)	(-1.012)	(0.014)	(-0.352)	(-0.069)
DPO_Borrower	-0.246	0.462	-0.149	0.037	-0.077	-0.089
	(-0.558)	(0.358)	(-0.219)	(0.808)	(-1.395)	(-1.006)
EBITDA_Borrower	-0.269**	-0.549*	-0.287**	-0.006	-0.016	-0.032*
	(-2.357)	(-1.808)	(-2.074)	(-0.841)	(-1.533)	(-1.744)
INTAN_Borrower	0.068	0.226	0.177	0.020**	0.005	0.005
	(0.587)	(0.788)	(1.276)	(2.077)	(0.366)	(0.264)
PPE_Borrower	0.012	-0.003	0.141	0.016	-0.003	-0.003
	(0.078)	(-0.008)	(0.786)	(1.391)	(-0.177)	(-0.116)
ΔSALES_Borrower	0.018	0.056	0.047**	0.001	0.002	0.001
	(1.076)	(1.350)	(2.216)	(0.563)	(0.841)	(0.302)
GDP_Borrower	-0.012	0.468	-0.128	-0.038**	-0.005	-0.009
	(-0.055)	(0.844)	(-0.535)	(-2.234)	(-0.196)	(-0.215)
ΔGDP_Borrower	0.008*	0.013	0.012**	0.000	0.000	-0.000
	(1.695)	(0.987)	(2.017)	(0.729)	(0.068)	(-0.297)
Constant	-41.018***	-103.337***	-56.918***	3.626***	-6.773***	-5.699***
	(-5.909)	(-6.312)	(-6.436)	(5.663)	(-9.410)	(-5.255)
Bank FE	Yes	Yes	Yes	Yes	Yes	Yes
Borrower FE	Yes	Yes	Yes	Yes	Yes	Yes
Year FE	Yes	Yes	Yes	Yes	Yes	Yes
Observations	7,830	7,830	7,830	7,830	7,830	7,830
Adjusted R^2	0.945	0.907	0.953	0.953	0.967	0.938

Table 7: Alternative Climate Risk Measure: Germanwatch Method

This table reports test results of the impact of the banks' climate risk exposure on their tail and systemic risks based on the use of an alternative climate risk measure computed using the Germanwatch method. The regressions include bank, borrower and year fixed effects (not reported). Standard errors are adjusted for clustering at the bank-borrower (lending relationship) level. ***, ** and * indicate statistical significance at the 1%, 5%, and 10% levels, respectively. Robust t-statistics are reported in parentheses. Variables are defined in Appendix A.

	(1) −TAIL5	(2) −TAIL1	(3) −MES	(4) −LRMES	(5) −ΔCoVaR5	(6) −ΔCoVaR1
CRI_Bank_GW	0.025	0.122*	0.206***	0.016***	0.019***	0.024***
	(0.970)	(1.723)	(5.642)	(5.792)	(5.899)	(4.287)
SIZE_Bank	-0.604***	-1.286***	-0.705***	-0.016	-0.046***	0.083***
	(-6.266)	(-4.461)	(-4.772)	(-1.621)	(-3.389)	(4.736)
EQRAT_Bank	-13.437***	-5.886	-7.241***	-0.935***	1.497***	2.536***
	(-7.437)	(-1.398)	(-2.829)	(-3.873)	(8.352)	(9.245)
MTB_Bank	-0.742***	-1.729***	-0.616***	-0.032***	-0.017**	0.040***
	(-9.291)	(-8.142)	(-6.389)	(-4.143)	(-2.354)	(3.539)
LTA_Bank	0.556*	-1.757**	1.423***	-0.012	0.311***	0.414***
	(1.659)	(-2.254)	(3.845)	(-0.428)	(7.862)	(7.401)
LLP_Bank	5.671	124.453***	46.045***	7.237***	4.241***	-5.436***
	(0.591)	(6.283)	(4.220)	(7.283)	(4.178)	(-3.253)
DEPO_Bank	-1.756***	-2.983***	-2.159***	-0.074**	-0.114**	0.004
	(-4.385)	(-2.615)	(-4.236)	(-2.327)	(-2.413)	(0.056)
NII_Bank	30.590***	7.882	57.726***	3.001***	4.175***	6.742***
	(5.848)	(0.690)	(9.324)	(6.044)	(8.008)	(8.652)
ROA_Bank	-68.528***	-51.364***	-108.542***	-5.826***	-5.204***	-10.139***
	(-8.889)	(-3.025)	(-11.841)	(-9.167)	(-7.622)	(-9.327)
OEM_Bank	7.333*	28.576***	-24.937***	-1.081***	-3.061***	-3.983***
	(1.761)	(2.928)	(-5.352)	(-3.961)	(-9.251)	(-6.369)
ΔCIR_Bank	-0.275**	-0.568*	-0.947***	-0.088***	0.020	0.071**
	(-2.030)	(-1.776)	(-5.381)	(-7.375)	(1.286)	(2.379)
GDP_Bank	5.053***	11.464***	6.716***	-0.190***	0.738***	0.449***
	(7.710)	(7.368)	(7.893)	(-2.958)	(10.582)	(4.591)
ΔGDP_Bank	0.062***	0.037**	-0.005	-0.004***	-0.006***	-0.010***
	(8.175)	(1.977)	(-0.525)	(-5.089)	(-8.775)	(-9.562)
SIZE_Borrower	0.005	-0.053	-0.018	-0.003**	-0.001	-0.004
	(0.282)	(-1.166)	(-0.833)	(-2.025)	(-0.410)	(-1.269)
MTB_Borrower	-0.015	-0.066*	-0.036**	-0.003**	-0.000	-0.003
	(-1.117)	(-1.895)	(-2.006)	(-2.003)	(-0.108)	(-1.282)
CASH_Borrower	0.024	0.340	0.299	0.016	0.006	-0.012
	(0.152)	(0.845)	(1.469)	(1.309)	(0.346)	(-0.474)
CURRENT_Borrower	-0.000	-0.001	0.004	0.001	-0.001	-0.001
	(-0.013)	(-0.025)	(0.160)	(0.255)	(-0.398)	(-0.241)
COVER_Borrower	0.000***	0.001	0.000*	0.000	0.000	0.000
	(2.632)	(1.233)	(1.703)	(0.665)	(0.355)	(0.283)
DEBT_Borrower	-0.086	-0.342**	-0.074	0.001	-0.003	-0.001
	(-1.468)	(-2.135)	(-0.990)	(0.141)	(-0.350)	(-0.053)
DPO_Borrower	-0.227	0.491	-0.141	0.053	-0.080	-0.089
	(-0.516)	(0.381)	(-0.207)	(1.147)	(-1.442)	(-1.005)
EBITDA_Borrower	-0.270**	-0.556*	-0.299**	-0.007	-0.017*	-0.033*
	(-2.370)	(-1.833)	(-2.176)	(-0.871)	(-1.679)	(-1.849)
INTAN_Borrower	0.066	0.225	0.183	0.018*	0.006	0.006
	(0.568)	(0.787)	(1.326)	(1.832)	(0.452)	(0.304)
PPE_Borrower	0.007	-0.012	0.133	0.013	-0.003	-0.003
	(0.049)	(-0.033)	(0.747)	(1.076)	(-0.175)	(-0.147)
ΔSALES_Borrower	0.018	0.054	0.043**	0.001	0.002	0.001
	(1.061)	(1.307)	(2.077)	(0.511)	(0.688)	(0.184)
GDP_Borrower	-0.013	0.456	-0.154	-0.038**	-0.008	-0.012
	(-0.060)	(0.821)	(-0.639)	(-2.163)	(-0.292)	(-0.290)
ΔGDP_Borrower	0.008*	0.013	0.012*	0.000	-0.000	-0.000
	(1.675)	(0.958)	(1.932)	(0.557)	(-0.024)	(-0.381)
Constant	-41.237***	-102.947***	-55.299***	3.371***	-6.534***	-5.488***
	(-5.962)	(-6.394)	(-6.313)	(5.166)	(-9.036)	(-5.029)
Bank FE	Yes	Yes	Yes	Yes	Yes	Yes
Borrower FE	Yes	Yes	Yes	Yes	Yes	Yes
Year FE	Yes	Yes	Yes	Yes	Yes	Yes
Observations	7,830	7,830	7,830	7,830	7,830	7,830
Adjusted R^2	0.944	0.907	0.953	0.951	0.967	0.938

Table 8: Interaction Tests

The regressions include bank, borrower and year fixed effects (not reported). Standard errors are adjusted for clustering at the bank-borrower (lending relationship) level. ***, ** and * indicate statistical significance at the 1%, 5%, and 10% levels, respectively. Robust *t*-statistics are reported in parentheses. Variables are defined in Appendix A.

	(1) −TAIL5	(2) −TAIL1	(3) −MES	(4) −LRMES	(5) −ΔCoVaR5	(6) −ΔCoVaR1
Loan Share	-0.015	-0.026	0.012	-0.004***	-0.000	0.000
	(-1.389)	(-0.907)	(0.946)	(-4.720)	(-0.291)	(0.074)
CRI_State_High	-0.074***	-0.215***	-0.102***	-0.009***	-0.002	-0.005
	(-3.309)	(-3.680)	(-3.748)	(-4.568)	(-0.895)	(-1.287)
Loan Share×CRI_State_High	0.065***	0.151***	0.081***	0.011***	0.006***	0.007***
	(7.559)	(6.966)	(7.444)	(12.032)	(5.406)	(4.642)
SIZE_Bank	-0.591***	-1.205***	-0.562***	-0.005	-0.033**	0.100***
	(-6.434)	(-4.499)	(-4.125)	(-0.559)	(-2.534)	(6.233)
EQRAT_Bank	-13.662***	-6.518	-7.995***	-0.983***	1.438***	2.460***
	(-7.526)	(-1.545)	(-3.077)	(-3.986)	(8.031)	(9.029)
MTB_Bank	-0.746***	-1.742***	-0.636***	-0.034***	-0.020***	0.037***
	(-9.350)	(-8.230)	(-6.606)	(-4.357)	(-2.670)	(3.286)
LTA_Bank	0.585*	-1.688**	1.493***	-0.007	0.318***	0.421***
	(1.746)	(-2.157)	(3.997)	(-0.227)	(8.242)	(7.592)
LLP_Bank	5.544	121.047***	37.665***	6.644***	3.428***	-6.475***
	(0.589)	(6.249)	(3.422)	(6.685)	(3.387)	(-4.001)
DEPO_Bank	-1.739***	-2.727***	-1.603***	-0.034	-0.061	0.071
	(-4.540)	(-2.626)	(-3.449)	(-1.110)	(-1.357)	(1.130)
NII_Bank	30.514***	8.565	59.674***	3.173***	4.386***	7.008***
	(5.817)	(0.753)	(9.550)	(6.445)	(8.628)	(9.122)
ROA_Bank	-68.241***	-50.850***	-108.328***	-5.823***	-5.206***	-10.139***
	(-8.888)	(-3.008)	(-11.848)	(-9.182)	(-7.579)	(-9.251)
OEM_Bank	7.437*	29.592***	-22.717***	-0.960***	-2.871***	-3.733***
	(1.828)	(3.100)	(-5.067)	(-3.501)	(-8.552)	(-6.050)
ΔCIR_Bank	-0.290**	-0.619*	-0.991***	-0.090***	0.017	0.067**
	(-2.141)	(-1.933)	(-5.679)	(-7.624)	(1.112)	(2.236)
GDP_Bank	4.958***	11.237***	6.526***	-0.199***	0.727***	0.435***
	(7.586)	(7.273)	(7.691)	(-3.045)	(10.311)	(4.424)
ΔGDP_Bank	0.064***	0.041**	-0.001	-0.004***	-0.006***	-0.010***
	(8.312)	(2.159)	(-0.138)	(-4.600)	(-8.254)	(-9.019)
SIZE_Borrower	0.001	-0.063	-0.028	-0.004**	-0.001	-0.005
	(0.037)	(-1.373)	(-1.235)	(-2.269)	(-0.653)	(-1.489)
MTB_Borrower	-0.017	-0.072**	-0.042**	-0.003**	-0.001	-0.004
	(-1.269)	(-2.065)	(-2.319)	(-2.245)	(-0.378)	(-1.514)
CASH_Borrower	0.034	0.361	0.310	0.018	0.006	-0.011
	(0.216)	(0.900)	(1.523)	(1.411)	(0.399)	(-0.432)
CURRENT_Borrower	0.001	0.002	0.007	0.001	-0.001	-0.001
	(0.046)	(0.043)	(0.256)	(0.354)	(-0.364)	(-0.204)
COVER_Borrower	0.000***	0.001	0.000*	0.000	0.000	0.000
	(2.761)	(1.298)	(1.776)	(0.771)	(0.394)	(0.317)
DEBT_Borrower	-0.087	-0.346**	-0.072	0.000	-0.002	-0.000
	(-1.506)	(-2.171)	(-0.961)	(0.074)	(-0.330)	(-0.033)
DPO_Borrower	-0.206	0.569	-0.043	0.060	-0.072	-0.079
	(-0.467)	(0.441)	(-0.063)	(1.277)	(-1.312)	(-0.892)
EBITDA_Borrower	-0.267**	-0.548*	-0.290**	-0.005	-0.016	-0.032*
	(-2.336)	(-1.799)	(-2.114)	(-0.632)	(-1.528)	(-1.746)
INTAN_Borrower	0.076	0.240	0.185	0.018*	0.006	0.006
	(0.658)	(0.838)	(1.335)	(1.884)	(0.471)	(0.311)
PPE_Borrower	0.006	-0.025	0.116	0.013	-0.003	-0.004
	(0.043)	(-0.067)	(0.651)	(1.099)	(-0.195)	(-0.183)
ΔSALES_Borrower	0.018	0.058	0.048**	0.001	0.002	0.001
	(1.108)	(1.396)	(2.291)	(0.696)	(0.829)	(0.316)
GDP_Borrower	-0.040	0.463	-0.167	-0.044**	-0.016	-0.018
	(-0.176)	(0.805)	(-0.668)	(-2.467)	(-0.559)	(-0.456)
ΔGDP_Borrower	0.008	0.011	0.011*	0.000	-0.000	-0.000
	(1.584)	(0.851)	(1.795)	(0.542)	(-0.001)	(-0.389)
Constant	-40.047***	-101.762***	-55.410***	3.374***	-6.552***	-5.532***
	(-5.777)	(-6.255)	(-6.286)	(5.039)	(-8.946)	(-5.077)
Loan Share +	0.050***	0.125***	0.093***	0.007***	0.005***	0.007***
Loan Share×CRI_State_High	(4.020)	(3.810)	(5.950)	(5.930)	(3.450)	(3.190)
Bank FE	Yes	Yes	Yes	Yes	Yes	Yes
Borrower FE	Yes	Yes	Yes	Yes	Yes	Yes
Year FE	Yes	Yes	Yes	Yes	Yes	Yes
Observations	7,830	7,830	7,830	7,830	7,830	7,830
Adjusted R^2	0.945	0.907	0.953	0.951	0.967	0.938

Table 9: Alternative Systemic Risk Measures: GARCH–ΔCoVaR

This table reports test results of the impact of the banks' climate risk exposure on their systemic risks estimated using the bivariate diagonal GARCH model. The regressions include bank, borrower and year fixed effects (not reported). Standard errors are adjusted for clustering at the bank-borrower (lending relationship) level. ***, ** and * indicate statistical significance at the 1%, 5%, and 10% levels, respectively. Robust *t*-statistics are reported in parentheses. Variables are defined in Appendix A.

	(1) GARCH−ΔCoVaR5	(2) GARCH−ΔCoVaR1
CRI_Bank	0.016**	0.023**
	(2.353)	(2.353)
SIZE_Bank	0.043	0.061
	(1.204)	(1.204)
EQRAT_Bank	0.024	0.034
	(0.026)	(0.026)
MTB_Bank	0.127***	0.180***
	(4.104)	(4.104)
LTA_Bank	0.128	0.181
	(1.309)	(1.309)
LLP_Bank	-0.175	-0.247
	(-0.049)	(-0.049)
DEPO_Bank	-0.034	-0.048
	(-0.146)	(-0.146)
NII_Bank	-2.457*	-3.475*
	(-1.652)	(-1.652)
ROA_Bank	-5.875	-8.309
	(-1.575)	(-1.575)
OEM_Bank	-8.135***	-11.506***
	(-5.759)	(-5.759)
ΔCIR_Bank	0.049	0.069
	(0.631)	(0.631)
GDP_Bank	-1.165***	-1.647***
	(-4.509)	(-4.509)
ΔGDP_Bank	-0.003	-0.005
	(-0.824)	(-0.824)
SIZE_Borrower	-0.001	-0.002
	(-0.172)	(-0.172)
MTB_Borrower	-0.003	-0.004
	(-0.386)	(-0.386)
CASH_Borrower	0.068	0.096
	(1.258)	(1.258)
CURRENT_Borrower	-0.012	-0.018
	(-1.349)	(-1.349)
COVER_Borrower	0.000	0.000
	(0.562)	(0.562)
DEBT_Borrower	0.031	0.044
	(1.119)	(1.119)
DPO_Borrower	-0.077	-0.109
	(-0.512)	(-0.512)
EBITDA_Borrower	-0.022	-0.031
	(-0.561)	(-0.561)
INTAN_Borrower	0.031	0.044
	(0.659)	(0.659)
PPE_Borrower	-0.028	-0.040
	(-0.534)	(-0.534)
ΔSALES_Borrower	0.004	0.006
	(1.005)	(1.005)
GDP_Borrower	0.100	0.141
	(0.965)	(0.965)
ΔGDP_Borrower	-0.001	-0.001
	(-0.521)	(-0.521)
Constant	12.691***	17.949***
	(4.743)	(4.743)
Bank FE	Yes	Yes
Borrower FE	Yes	Yes
Year FE	Yes	Yes
Observations	1,983	1,983
Adjusted R^2	0.975	0.975

Table 10: Weighted Least Squares

This table reports test results of the impact of the banks' climate risk exposure on their tail and systemic risks using Weighted Least Squares (WLS) estimation. Panel A reports results using state population of lender banks as the weight in WLS estimation. Panel B reports results using banks' market capitalization as the weight in WLS estimation. The regressions include bank, borrower and year fixed effects (not reported). Standard errors are adjusted for clustering at the bank-borrower (lending relationship) level. ***, ** and * indicate statistical significance at the 1%, 5%, and 10% levels, respectively. Robust t-statistics are reported in parentheses. Variables are defined in Appendix A.

Panel A. Weighted Least Squares (by State Population of Lender Banks)

	(1) −TAIL5	(2) −TAIL1	(3) −MES	(4) −LRMES	(5) −ΔCoVaR5	(6) −ΔCoVaR1
CRI_Bank	0.031**	0.080**	0.087***	0.025***	0.004**	0.010***
	(2.044)	(2.138)	(4.495)	(15.015)	(1.980)	(2.853)
Constant	-41.787***	-105.039***	-57.162***	3.650***	-6.829***	-5.787***
	(-6.135)	(-6.444)	(-6.520)	(5.790)	(-9.546)	(-5.365)
Controls	Yes	Yes	Yes	Yes	Yes	Yes
Bank FE	Yes	Yes	Yes	Yes	Yes	Yes
Borrower FE	Yes	Yes	Yes	Yes	Yes	Yes
Year FE	Yes	Yes	Yes	Yes	Yes	Yes
Observations	7,830	7,830	7,830	7,830	7,830	7,830
Adjusted R^2	0.945	0.907	0.953	0.953	0.967	0.938

Panel B. Weighted Least Squares (by Bank Market Capitalization)

	(1) −TAIL5	(2) −TAIL1	(3) −MES	(4) −LRMES	(5) −ΔCoVaR5	(6) −ΔCoVaR1
CRI_Bank	0.029**	0.086**	0.091***	0.026***	0.003*	0.008**
	(1.968)	(2.365)	(4.850)	(16.021)	(1.815)	(2.506)
Constant	-45.707***	-111.530***	-61.885***	3.608***	-7.233***	-6.618***
	(-6.677)	(-6.902)	(-7.370)	(6.255)	(-10.271)	(-6.266)
Controls	Yes	Yes	Yes	Yes	Yes	Yes
Bank FE	Yes	Yes	Yes	Yes	Yes	Yes
Borrower FE	Yes	Yes	Yes	Yes	Yes	Yes
Year FE	Yes	Yes	Yes	Yes	Yes	Yes
Observations	7,830	7,830	7,830	7,830	7,830	7,830
Adjusted R^2	0.947	0.909	0.954	0.956	0.968	0.938

Table 11: Standard Errors

This table reports test results of the impact of the banks' climate risk exposure on their tail and systemic risks. Panel A reports results with standard errors adjusted for clustering at the borrower state level. Panel B reports results with heteroskedasticity- and autocorrelation-consistent (HAC) standard errors computed following the Newey and West (1987) procedure that allows for up to two periods of autocorrelation. The regressions include bank, borrower and year fixed effects (not reported). ***, ** and * indicate statistical significance at the 1%, 5%, and 10% levels, respectively. Robust *t*-statistics are reported in parentheses. Variables are defined in Appendix A.

Panel A. Standard Errors Clustered at Borrower State Level

	(1) $-$TAIL5	(2) $-$TAIL1	(3) $-$MES	(4) $-$LRMES	(5) $-\Delta$CoVaR5	(6) $-\Delta$CoVaR1
CRI_Bank	0.031*	0.080	0.087***	0.025***	0.004*	0.009***
	(1.819)	(1.405)	(3.302)	(9.558)	(1.936)	(2.858)
Constant	-41.018***	-103.337***	-56.918***	3.626***	-6.773***	-5.699***
	(-4.750)	(-5.230)	(-5.097)	(5.485)	(-5.824)	(-3.649)
Controls	Yes	Yes	Yes	Yes	Yes	Yes
Bank FE	Yes	Yes	Yes	Yes	Yes	Yes
Borrower FE	Yes	Yes	Yes	Yes	Yes	Yes
Year FE	Yes	Yes	Yes	Yes	Yes	Yes
Observations	7,830	7,830	7,830	7,830	7,830	7,830
Adjusted R^2	0.945	0.907	0.953	0.953	0.967	0.938

Panel B. Newey-West Standard Errors

	(1) $-$TAIL5	(2) $-$TAIL1	(3) $-$MES	(4) $-$LRMES	(5) $-\Delta$CoVaR5	(6) $-\Delta$CoVaR1
CRI_Bank	0.031**	0.080**	0.087***	0.025***	0.004**	0.009***
	(2.219)	(2.288)	(4.855)	(15.855)	(1.988)	(3.080)
Constant	-40.371***	-102.868***	-55.688***	3.568***	-6.926***	-5.434***
	(-6.863)	(-6.963)	(-7.594)	(6.629)	(-10.761)	(-5.659)
Controls	Yes	Yes	Yes	Yes	Yes	Yes
Bank FE	Yes	Yes	Yes	Yes	Yes	Yes
Borrower FE	Yes	Yes	Yes	Yes	Yes	Yes
Year FE	Yes	Yes	Yes	Yes	Yes	Yes
Observations	7,830	7,830	7,830	7,830	7,830	7,830
Adjusted R^2	0.945	0.907	0.953	0.953	0.967	0.938

Appendix A. Variable Definition

Variable	Definition	Source
Climate Risk Measures		
CRI_State	State-level climate risk calculated based on the Billion-Dollar Weather and Climate Disasters data by the National Centers for Environmental Information (NOAA). It is defined as the first principal component of six key climate risk indicators: (1) number of death, (2) number of deaths per 100,000 inhabitants, (3) sum of losses in USD at purchasing power parity (PPP), (4) losses per unit of Gross Domestic Product (GDP), (5) number of events, and (6) loss per event.	BEA NOAA
CRI_State_GW	State-level climate risk calculated using the Germanwatch method. It is defined as the sum of the state's score in all four indicating categories: (1) number of deaths, (2)number of deaths per 100,000 inhabitants, (3) sum of losses in USD at PPP, (4) losses per unit of GDP, (5) number of events, and (6) loss per event.	As above
CRI_Bank	Bank-level climate risk. The sum of a bank's lending to individual state as a percentage of its total lending weighted by CRI_State of the specific state for each year.	BEA NOAA Dealscan
CRI_Bank_Adj	Bank-level climate risk adjusting for borrower firms' vulnerability to climate change.	As above
CRI_Bank_Res	Bank-level residual climate risk. The residual imputed from regressing CRI_Bank on a set of market-based common risk factors including market risk, market risk for banking industry, credit risk, commodity risk, political risk, real estate risk, and sovereign risk.	As above
CRI_Bank_GW	Bank-level climate risk calculated based on CRI_State_GW.	As above
Dependent Variables		
TAIL5	The average return for a bank during the 5% worst return days for the bank in a year.	CRSP
TAIL1	The average return for a bank during the 1% worst return days for the bank in a year.	As above
MES	Marginal expected shortfall. The average return for a bank during the 5% worst return days for the banking industry in a year.	As above
LRMES	Long-run marginal expected shortfall during the 2% worst return days for the banking industry in a year.	As above

Variable	Definition	Source
ΔCoVaR5	A measure of a bank's marginal contribution to the risk of the system, computed as the difference between the value at risk of the system when the institution's return is at the 5^{th} percentile and the value at risk of the system when the institution' return is at the median.	As above
ΔCoVaR1	A measure of a bank's marginal contribution to the risk of the system, computed as the difference between the value at risk of the system when the institution's return is at the 1^{st} percentile and the value at risk of the system when the institution' return is at the median.	As above
Lender Characteristics		
SIZE_Bank	Bank size. Natural logarithm of total assets (*at*).	Compustat
EQRAT_Bank	Equity ratio. Book value of equity (*ceq*) divided by total assets (*at*).	As above
MTB_Bank	Market-to-book ratio. Market value of equity (*prccm*×*cshom*) divided by book value of equity (*ceq*).	As above
LTA_Bank	Loans-to-assets ratio. Loans net of total allowance for loan losses (*lntal*) divided by total assets (*at*).	As above
LLP_Bank	Loan loss provisioning. Provisions for loan or asset losses (*pll*) divided by total assets (*at*).	As above
DEPO_Bank	Deposit ratio. Total deposits (*dptc*) divided by total assets (*at*).	As above
NII_Bank	Noninterest income ratio. Total noninterest income (*tnii*) divided by total assets (*at*).	As above
ROA_Bank	Return on assets. Net income (*ni*) divided by total assets (*at*).	As above
OEM_Bank	Operating expense management. Total current operating expenses (*tcoe*) divided by total assets (*at*).	As above
ΔCIR_Bank	Change in cost-to-income ratio. Cost to income ratio is calculate as dividing total current operating expenses (*tcoe*) by gross total revenue (*tcor*).	As above
Borrower Characteristics		
SIZE_Borrower	Firm size. Natural logarithm of total assets (*at*).	Compustat
MTB_Borrower	Market-to-book ratio. Market value of equity (*prcc_f*×*csho*) divided by book value of equity (*ceq*).	As above
CASH_Borrower	Cash holding ratio. Cash and short-term investments (*che*) divided by total assets (*at*).	As above
CURRENT_Borrower	Current ratio. Current assets (*aco*) divided by current liabilities (*lco*).	As above

Variable	Definition	Source
COVER_Borrower	Interest coverage. Earnings before interest (*ebitda*) divided by total interest expense (*xint*).	As above
DPO_Borrower	Dividend payout ratio. The sum of dividends paid to ordinary shares (*dvc*) and dividends paid to preferred shares (*dvp*) divided by total assets (*at*).	As above
EBIDTDA_Borrower	Earnings before interest, taxes, depreciation, and amortization (*ebidtda*) divided by sales (*sale*).	As above
INTAN_Borrower	Intangible assets ratio. Intangible assets (*intan*) divided by total assets (*at*).	As above
PPE_Borrower	Fixed assets ratio. Property, plant and equipment (*ppent*) divided by total assets (*at*).	As above
ΔSALES_Borrower	Annual growth in sales revenue (*sale*).	As above
State-Level Variables		
GDP_Bank	Natural logarithm of annual gross domestic product (GDP) per capita of the bank's state.	BEA
ΔGDP_Bank	Annual growth rate of GDP per capita of the bank's state.	As above
GDP_Borrower	Natural logarithm of annual GDP per capita of the firm's state.	As above
ΔGDP_Borrower	Annual growth rate of GDP per capita of the firm's state.	As above
Instrumental Variables		
FOREIGN	Foreign loans. Foreign loans (*lft*) divided by total loans (*lntal*).	Compustat
POP	Population density. The population of a state in a given year divided by the land area of the state.	St. Louis Fed

Appendix B. Industry Classification by Climate Change Vulnerability

High	Medium	Low
Coal	Agriculture	Real estate
Oil and gas	Automotive	Telecommunication carriers
Shipping and aviation	Electronics	Rail systems
Construction (incl. cement)	Retail stores (incl. warehouses)	Renewable power generation
Freight transport	Metal mining	Natural gas extraction
Livestock	Iron and steel production	
Aluminium production		

Source: ING (2020)

Appendix C. Common Risk Factors

Risk Factor	Description	Source
Interest rate risk	Percentage changes in the market value of long-term assets. The factor is based on market prices of 10–year government bonds.	Datastream
Credit risk	Changes in the default premium between BAA– and AAA–rated corporate bonds. The factor is based on time series maintained by Moody's.	Datastream
Commodity risk	Percentage changes in the S&P GSCI Total Return Index.	Datastream
Foreign exchange risk	Percentage changes in the trade-weighted currency baskets. The factor measures the currency value with respect to the currency values of the major trade partners.	Bank of England
Market risk	Percentage changes in the market value of S&P 500.	Datastream
Market risk (banking industry)	Percentage changes in the market value of the banking sector stock market portfolios.	Datastream
Political risk	Percentage changes in gold price against U.S. dollars.	Bank of England
Real estate risk	Percentage changes in the market value of the REIT investments.	Datastream
Sovereign risk	Changes in the difference of the (mean) of yields on the 10–year government bonds (Greece, Portugal, Spain, Italy) and 10–year German Government bonds.	Datastream
VIX	Chicago Board Options Exchange volatility index. The index measures market expectations of short-term volatility based on S&P 500 stock-index option prices.	Datastream