Systemic Climate Risk

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Abstract

This paper introduces a market-based framework to study the effects of tail climate risks in the financial sector. We identify the financial institutions most exposed to physical and transition climate-related shocks, and analyze how these shocks may propagate through the financial network and amplify systemic risk. Using security-level data on large European financial institutions from 2005 to 2022, we show that transition risk, unlike physical risk, significantly and increasingly contributes to systemic risk. We also examine the potential levers available to financial institutions and regulators to address climate-related financial risk.

JEL Classification: G10, G20, G32, Q54

Keywords: Climate risk, contagion, ESG, financial stability, systemic risk

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1. Introduction

In 2015, the governor of the Bank of England, Mark Carney, warned that climate change had the potential to profoundly affect asset prices and financial stability (Carney, 2015). While the systemic impact of climate risks remains uncertain, it has become a central concern in the financial community (Stroebel and Wurgler, 2021). Climate risks are typically categorized into two main types: physical and transition risks.[1] These risks can negatively and differentially affect financial institutions, leading to losses in financial portfolios, heightened claims paid by insurers, or diminished borrower creditworthiness. These direct impacts of climate risks on financial institutions are referred to as first-round effects.

Beyond direct exposures, climate-related shocks may propagate through the financial system via common asset holdings, fire-sale dynamics, or balance sheet linkages. These second-round effects amplify the initial impact of climate shocks and pose additional threats to financial stability. We term the combined first- and second-round threats posed to the financial system by climate hazards as systemic climate risks. This concept aligns with theoretical models of financial contagion and systemic amplification through risk-sharing frictions and liquidity spirals (e.g., Allen and Gale, 2000; Acemoglu et al., 2015; Brunnermeier and Pedersen, 2009; Greenwood et al., 2015). In these models, interconnections among institutions exacerbate tail events. If climate-related tail losses are large and information is imperfect, a precautionary approach may be needed to maximize social welfare (Weitzman, 2009), for instance, through strengthened regulation or macroprudential supervision.

[1] Physical risk stems from the effects of climate change and climate-related hazards (e.g., heat waves, extreme precipitation, wildfires, etc.). Transition risk arises from changes in stakeholder preferences, changes in regulation, legal exposure from contributing to climate change, and climate-related technological disruptions (Krueger et al., 2020, Stroebel and Wurgler, 2021).

In this paper, we introduce an innovative market-based framework to assess the influence of climate risks on systemic risk in the financial sector. Our approach builds on the asset pricing literature, which holds that market prices embed forward-looking assessments of risk and expected returns, including climate-related risks (e.g., Pástor et al., 2021). The framework distinguishes between individual tail risk and tail dependence among financial institutions, enabling us to disentangle first- and second-round effects of climate shocks. While a recent study by Jung et al. (2025) introduces CRISK, an indicator designed to capture the first-round effects of transition risk on the banking sector, it does not assess potential contagion effects arising from these risks. Our approach addresses this gap by developing a test procedure for detecting and quantifying the second-round effects of climate risks on financial institutions. We believe that this feature is crucial for assessing the level of systemic risk within the financial sector (e.g., Billio et al., 2012; Duarte and Eisenbach, 2021).[2] On the basis of this framework, we estimate the effects of both transition and physical risks on various types of financial institutions—banks, insurers, financial services companies, and real estate investment firms—and on various countries to capture both cross-border and cross-sectoral transmission and amplification channels. In contrast to the literature, we aim to provide a comprehensive evaluation of systemic climate risk in the financial sector.

Framework.—We proceed with the following steps. *First*, for our study, we design a systemic risk measure related to the methods suggested by Adams et al. (2014), Adrian and Brunnermeier (2016), and Kelly and Jiang (2014). The specificity of our approach lies in its

[2] The Financial Stability Board highlights the need for "identifying systemic risks to inform a macroprudential perspective, in addition to a microprudential perspective, to comprehensively consider the nature, scale and severity of climate-related risks to financial institutions individually and to the financial system collectively. Systemic risks arising from climate change can include second order effects and risk transfers or spillovers between financial sectors [...]." (FSB, 2022, Supervisory and Regulatory Approaches to Climate-related Risks, October). The recent Fit-for-55 climate scenario analysis by the European Supervisory Authorities and the European Central Bank shows that the second-round effects of climate risks may be large (https://www.ecb.europa.eu/pub/pdf/other/ecb.report_fit-for-55_stress_test_exercise%7E7fec18f3a8.en.pdf).

ability to discern between two fundamental elements of systemic risk: individual tail risk and tail dependence. This distinction is crucial for studying and differentiating the first- and second-round effects of climate risks on the financial sector. Moreover, our approach enables the estimation of covariations in tail risks among a vast array of financial institutions, thereby reflecting both cross-sectoral and cross-border shocks. Using market data, we derive time-varying measures of individual tail risk for each financial institution, coupled with a dynamic indicator of systemic risk that captures common shifts in financial institution tails. Thus, our methodology offers a comprehensive view of both individual and interconnected risk dynamics.

Second, we develop climate-specific tail risk factors for both transition and physical risks. Climate risks are inherently forward-looking and characterized by uncertainty and fat tails due to nonlinear features such as tipping points (e.g., Barnett et al., 2020; Hansen, 2022; Weitzman, 2009). Our tail climate risk factors aim to measure the expected impact of extreme climate shocks on the value of nonfinancial firms, to which financial institutions are exposed through loans, portfolio holdings, or insurance contracts. To develop these factors, we use a large sample of stocks issued by nonfinancial companies, sorting firms based on specific climate-related characteristics and constructing long–short factor-mimicking portfolios. Tail risk factors are then derived parametrically from the returns of these portfolios, capturing the global uncertainty and fat-tailed distribution of climate risks. We use these tail risk factors in regression analysis to evaluate the sensitivity of financial institutions to extreme climate shocks through their exposure to nonfinancial firms.

Third, we propose a two-pass test procedure to assess whether climate risks exacerbate tail risk dependence among financial institutions. Our procedure builds on the literature that explores the use of principal components in asset pricing and systemic risk analysis (e.g., Billio et al., 2012; Giglio and Xu, 2021; Kozak et al., 2018; Pukthuangthong et al., 2019) and is specifically tailored to examine the determinants of tail risk dependencies. In the first phase of our test procedure, we conduct time series regressions to determine whether increases in climate risks are associated with simultaneous rises in downside risk in the financial sector. We complement this with a cross-sectional test that links institutions' exposure to climate risks to their contributions to systemic risk.

Fourth, we investigate how financial and extrafinancial characteristics of financial institutions relate to climate risk exposure. This includes environmental, social and governance (ESG) disclosures, Scope 3 emissions, board incentive structures, and institutional ownership. We also examine the impact of country-level climate conditions and ESG regulatory shocks on risk exposures. In essence, the purpose of this fourth step is to determine whether the pricing of climate risks incorporates financial and extrafinancial information, and how institutions respond to their climate risk exposure. Understanding these associations is essential for guiding regulators and practitioners in mitigating systemic climate risk.

Overall, our market-based framework provides a flexible and dynamic tool for evaluating the emergence of systemic climate risk. At a time when the integration of climate risks into asset prices is becoming a major concern for regulators (IMF, 2020; NGFS, 2022), the proposed framework can help monitor whether climate risk is increasingly viewed as a financial stability threat. Specifically, our approach supports the construction of climate risk indicators that quantify and track, over time, the potential losses stemming from the direct and cascading effects of transition and physical risks. This indicator extends the work of Adrian and Brunnermeier (2016) and is akin to a "climate" exposure CoVaR[3] indicator (C-CoVaR), incorporating extreme climate risks as potential stress factors for financial institutions. The

[3] CoVaR here stands for conditional value-at-risk, i.e., the sensitivity of a financial institution's value at risk to an increase in climate risks.

forward-looking nature of market prices may also enable early detection of emerging financial vulnerabilities, offering a complementary perspective to research on climate scenario modeling and long-term projections of the impact of climate risks on the financial system (e.g., Battiston et al., 2017; Dietz et al., 2016; Roncoroni et al., 2021), as these projections face inherent uncertainty (Barnett et al., 2020).[4] Finally, in addition to supporting monitoring efforts, our approach provides actionable insights for financial institutions and supervisors aiming to mitigate systemic climate risk.

Overview of Results.—We apply our framework to a sample of 371 large European financial stocks, spanning from 2005 to 2022 at a monthly frequency and sourced from Refinitiv Datastream. We focus on Europe rather than the United States for several reasons. First, European investors may have stronger environmental concerns than their American counterparts do (see Amel-Zadeh and Serafeim, 2018).[5] Second, an escalation in systemic risk could yield more severe economic consequences in Europe, as the failure of European institutions is typically large relative to domestic GDP (Engle et al., 2015). Third, focusing on Europe allows us to leverage our access to confidential regulatory data from the Eurosystem on institutional holdings.

Our results indicate that transition risk has a significant effect on the tail risk of European financial institutions. Notably, we find that transition risk can amplify extreme risk dependence within the European financial sector, with the magnitude of these second-round effects being particularly pronounced in the latter half of the analyzed period. This finding constitutes, to our

[4] The first best approach to monitoring financial institutions would be to directly predict future outcomes. However, this first-best solution may not be implementable, as the probability distribution of climate risks remains imperfectly known (Weitzman, 2009). Therefore, we believe that our approach focused on ex ante vulnerability represents a more realistic solution.

[5] See also this report from the Global Sustainable Investment Alliance. The proportion of sustainable investing (relative to total assets under management) has been consistently higher in Europe than that in the US during 2014–2020.

knowledge, the first empirical evidence of potential contagion effects in the financial sector arising from climate shocks, whether from common risk exposures, spillovers, or pure contagion (Masson, 1998). Using dynamic estimates, we also show that the incorporation of transition risk as a systemic risk for the European financial sector has increased steadily since 2015, especially for banks and insurance companies, reaching a peak in 2021. In contrast, we do not find evidence of such contagion effects for physical climate risk. This result is in line with recent surveys (Krueger et al., 2020; Stroebel and Wurgler, 2021) that indicate that financial researchers and practitioners perceive the materialization of regulatory risk as more immediate than that of physical risk. Kahn et al. (2024) also find that financial institutions are able to reduce their exposure to certain physical risks, such as wildfires, by diversifying their portfolios geographically.

Looking at the characteristics of institutions that correlate with climate risks, we find that climate risk exposure is lower for financial institutions that engage in environmentally responsible initiatives. Using greenhouse gas (GHG) emission data, we show that institutions with cleaner investment and lending portfolios tend to be less exposed to transition risk. In addition, our analysis reveals a negative relationship between the long-term orientation of financial institutions and transition risk exposure through proxies such as institutional ownership and long-term incentives granted to board members. Climate risk exposure also correlates with country-level climate risk variables and country-year level ESG regulatory shocks. Additionally, our results indicate that financial institutions with greater exposure to transition risk tend to disclose more extrafinancial information through flexible channels. Finally, we observe that financial institutions react to physical risk by undertaking proactive risk management initiatives.

Related literature.—Our study is linked to the literature on the integration of climate risks into financial market prices. Many papers identify premiums associated with climate risks in equity markets (e.g., Ardia et al., 2022; Bolton and Kacperczyk, 2021; Choi et al., 2020; Görgen et al., 2020), real estate markets (e.g., Bernstein et al., 2019; Baldauf et al., 2020; Murfin and Spiegel, 2020) or bond markets (e.g., Flammer, 2021; Zerbib, 2019). Despite these findings, other articles indicate that climate risks remain underestimated by market participants, leading to market inefficiencies (e.g., Alok et al., 2020; Hong et al., 2019; Kruttli et al., 2025). Our study differs from this literature in that it looks at the effects of transition and physical climate shocks on market risk and comovements. To achieve this, it builds on the broader literature that seeks to uncover the risk factors driving stock returns and comovements, particularly through the use of principal components (e.g., Giglio and Xu, 2021; Kozak et al., 2018; Pukthuangthong et al., 2019). Methodologically, our contribution lies in proposing a flexible framework to identify risk factors reflected in the tail risk of equity markets. Although our study is focused on climate risks, we believe that the proposed framework is also applicable to the examination of other emerging risk factors.

Another strand of the literature focuses on the effect of environmental risks on financial stability. Lins et al. (2017) show that firms with good ESG ratings outperformed during the global financial crisis, whereas Ilhan et al. (2021) identify brown stocks as more exposed to tail downside risk on the basis of options market prices. Several articles delve into how certain ESG characteristics may help reduce the extreme risk of banks (Aevoae et al., 2022; Anginer et al., 2018; Kleymenova and Tuna, 2021; Scholtens and van't Klooster, 2019) and equity mutual funds (Cerqueti et al., 2021). Other studies focus on analyzing financial institutions' holdings of brown securities and loans (e.g., Alessi and Battiston, 2022; ECB-ESRB, 2021). Our framework is inherently more closely related to financial outcomes, investigating whether systemic climate risks are reflected in asset prices and whether climate-related shocks are propagating to and between financial institutions. Our main contributions to this literature are threefold. First, our study encompasses all types of financial institutions and addresses both transition and physical risks. Second, we pioneer the design of a test procedure to analyze whether climate risks affect the overall systemic risk in the financial sector, capturing second-round effects. This unique aspect of our framework addresses potential contagion effects across financial institutions, a key element of systemic risk often neglected by the related literature on climate finance.[6] Third, we introduce a new systemic climate risk indicator for financial institutions, the climate exposure CoVaR, derived from Adrian and Brunnermeier (2016), which monitors and quantifies the potential financial implications of climate shocks on the financial sector and distinguishes between first- and second-round effects.

Finally, our study makes a valuable contribution to the literature on the determinants of and reactions to climate risks. Several papers have examined how financial institutions adjust their operations in the aftermath of climate disasters (e.g., Ge and Weisbach, 2021; Manconi et al., 2016; Massa and Zhang, 2021; Schüwer et al., 2019). In addition, by using earnings call transcripts, Li et al. (2020) and Sautner et al. (2023) build firm-level measures of climate risks and investigate the characteristics that correlate with these measures and how firms respond to such risks. Our research takes a different approach and analyzes the determinants of investors' pricing of corporate climate risks. We find a limited correlation between our measure and that of Sautner et al. (2023) in our sample of financial institutions. This suggests that greater exposure to tail climate risks does not consistently translate into more in-depth discussions of these risks during earnings calls. Furthermore, to our knowledge, our study is the first to explore

[6] In another context and based on a different method, Yang et al. (2023) study transition risk spillovers among six major equity markets from 2013 to 2021.

a broad spectrum of potential characteristics associated with climate risk measures derived from market data. These include environmental and governance features, GHG emissions, and institutional ownership. We also extend the literature on the determinants of voluntary nonfinancial disclosure (e.g., Dhaliwal et al., 2011, Ilhan et al., 2023, Reid and Toffel, 2009) by testing whether financial institutions with high exposure to climate risks are inclined to disclose more information about these risks.

2. Data and methodology

2.1. Systemic risk measure

We define a measure of systemic risk within a system of *N* financial institutions based on common variations in their tail risk. Our baseline measure of tail risk is a time-varying 1-month 95%-value-at-risk (VaR) that we estimate from the stock returns of financial institutions on the basis of a GJR-GARCH model (see Appendix C). A 1-month 95%-VaR represents the negative return that is not exceeded during this month with a 95% probability. Alternative tail risk measures, such as the expected shortfall, can also be used.[7] Equity returns are meant to be informative about the risks of financial institutions and reflect information more quickly than accounting variables do. Furthermore, the use of tail risk measures meets our objective of analyzing whether climate risks threaten financial stability.

We extract common variations in individual tail risks based on a principal component analysis (PCA). The PCA is based on a decomposition of the matrix:

$$\Sigma_{\mathrm{std}} = \frac{1}{N-1}\,\Delta\mathrm{VaR}_{\mathrm{std}}^{T}\,\Delta\mathrm{VaR}_{\mathrm{std}} \tag{1}$$

[7] The choice of 95% VaR is common practice in the literature; however, the main conclusions of this study remain unchanged when different probability values are used. Nor are the conclusions affected by the use of an expected shortfall measure, instead of VaR, derived from the same GJR-GARCH model.

where Σ_{std} is the $N \times N$ correlation matrix between time variations in the VaR of financial institutions. In our framework, we use the first differences of the VaR (ΔVaR), which reflect changes in tail risk and ensure stationarity. $\Delta\mathrm{VaR}_{\mathrm{std}}$ is a $T \times N$ matrix of the standardized variables. Performing PCA on the correlation matrix ensures that relatively small institutions with high variance are not overrepresented. The eigendecomposition of Σ_{std} is as follows:

$$\Sigma_{\mathrm{std}} = \xi \Lambda \xi^{T} \tag{2}$$

where ξ is a $N \times N$ matrix that contains the normalized eigenvectors corresponding to the largest eigenvalues of Σ_{std} and where Λ is the diagonal matrix of eigenvalues.

Ω is a $T \times N$ matrix of principal components extracted from the correlation matrix Σ_{std}. The principal components are uncorrelated variables, which satisfy $\mathrm{E}[\Omega\Omega^{T}] = \Lambda$. The components are the projections of the standardized variables onto the eigenvector space:

$$\Omega = \Delta\mathrm{VaR}_{\mathrm{std}}\xi \tag{3}$$

The first principal component, Ω_1, serves as our time series estimator of systemic risk. It captures common shifts in tail risk across institutions, reflecting extreme risk dependence within the financial sector. We focus on the first principal component because it captures the most important shocks propagating through the financial sector. Subsequent principal components typically represent shocks affecting only a subset of financial institutions, making them less relevant for systemic risk analysis. Figure A.1 shows that Ω_1 explains 27.9% of the variance in the database, whereas Ω_2 explains 6.5% of the variance. The ten first components explain 53% of the variation. This finding is in line with other papers analyzing the factor structure of individual stock returns (e.g., Billio et al., 2012).

The contribution of financial institutions to systemic risk is measured as follows:

$$X_1 = \xi_1 \tag{4}$$

with X_1 a $N \times 1$ vector of factor loadings onto the first principal component, capturing the contribution (or, equivalently, the exposure) of each financial institution to global downside risk. Alternatively, we use the average correlation coefficient of each financial institution with the remaining financial sector computed from Σ_{std} as a systemic risk contribution measure, therefore reflecting the information of all principal components.

Our systemic risk measure shares similarities with that used in previous studies, namely, Adams et al. (2014), Adrian and Brunnermeier (2016), Billio et al. (2012), and Kelly and Jiang (2014). Nevertheless, the proposed indicator presents certain discrepancies with existing measures in terms of both target and methodology, making it more suitable for our study. First, in contrast to the rest of the literature, our systemic risk measure distinguishes between two important elements of systemic risk: individual tail risk and extreme dependence. We argue that this distinction is essential for studying both the first- and second-round effects of climate risks on the financial sector. Second, whereas the CoVaR indicator of Adrian and Brunnermeier (2016) aims to measure the contribution of each institution to the financial sector's tail risk, which can raise reverse causality issues, we directly estimate simultaneous changes in the VaR across all financial institutions. This approach allows us to place a stronger emphasis on the overall level of tail risk dependence, leaving aside the question of the directionality of spillovers. Our setup also shares similarities with that of Adams et al. (2014), as we first estimate the VaR of each financial institution and then investigate their comovements. The main originality of our approach lies in extracting common variations in individual tail risks based on a PCA. Therefore, unlike Adams et al. (2014), who examine VaR spillovers based on a vector autoregressive framework, our measure can estimate covariations in tail risk across many financial institutions.[8] This approach allows us to examine both cross-sectoral and cross-border shock transmission and amplification channels. Finally, our method is linked to that of Kelly and Jiang (2014), who directly estimate common dynamics in firms' tail risk using the cross-section of returns. An attractive feature of our measure compared with that of Kelly and Jiang (2014) is the ability to derive time-varying individual measures of tail risk.

We apply this approach to the entire sample of financial institutions from 2005 to 2022.[9] Although our primary measure of systemic risk is based on extreme comovements across all financial institutions, we can also extract specific measures for each type of financial institution. Figure A.2 represents the time-varying systemic risk indicator (Ω_1) for all institutions from February 2005 to April 2022. Large increases in systemic risk occurred after the bankruptcy of Lehman Brothers in September 2008, during the July–August 2011 Eurozone stock market crash, after the Brexit referendum in June 2016, and during the European COVID-19 outbreak in March 2020. Compared with the global financial crisis in 2008, the COVID-19 shock led to a more sudden increase in market volatility, which explains why an extremum was reached during the COVID-19 outbreak.

In addition, Table OA.1 shows the largest contributors to systemic risk. Among the top 30 contributors, banks are the most represented institutions (19 out of 30). Interestingly, the ranking of the most interconnected institutions shows notable differences when we estimate the dependence between returns or tail risk measures. Although real estate companies are absent

[8] Cooley and Thibaud (2019) also suggest an approach to extract principal components from a tail dependence matrix based on multivariate extreme value analysis. We believe that one advantage of working with time-varying VaR is that the estimation of tail dependence can be performed on the entire sample instead of a small number of extreme observations.

[9] The main results in the rest of this paper are robust to the use of sparse PCA, which helps manage the high cross-sectional dimensionality of the data by introducing sparsity structures to the input variables (unreported). Similarly, the main conclusions remain unchanged when we extract comovements by using dynamic PCA, which has been suggested as a remedy for high-dimensional and time-dependent data. The average correlation between systemic risk indicators obtained from standard PCA, sparse PCA, and dynamic PCA is over 98%.

from the sample based on returns, five real estate institutions appear in the rankings on the basis of tail risk. In addition, whereas 9 insurance companies are included in the sample based on returns, only 2 emerge when tail risk is considered. This difference between covariations based on returns and higher-order moments is consistent with the literature (e.g., Diebold and Yilmaz, 2009) and underscores the value of examining tail dependence to study systemic risk.

2.2. Climate risk factors

The climate finance literature has suggested several approaches to building climate risk indicators. Ardia et al. (2022) and Engle et al. (2020) apply natural language processing to assess the degree of media attention to climate change in newspapers. Choi et al. (2020) rely on Google Trends. Briere and Ramelli (2021) construct a climate stress indicator by using investor flows toward sustainable exchange-traded funds. Finally, in some articles, investors' attention to climate risks is explored by building long–short portfolios based on market and environmental variables (e.g., Görgen et al., 2020; Hsu, et al., 2023). We follow the latter approach, as it directly captures the effect of climate characteristics on nonfinancial equity returns. We then derive tail climate risk factors from long–short portfolio returns.

Factor construction

We construct two climate risk factors by using a large sample of dead and active European stocks (excluding financial sector companies). The factors are based on the monthly returns[10] of long–short portfolios following the standard approach in the asset pricing literature (e.g., Fama and French, 1993, 2015). Each month, we sort nonfinancial stocks into 5 quintile portfolios based on climate characteristics. We then calculate the return spread between the

[10] The use of monthly data is common practice in the empirical asset pricing literature, as it reduces the noise that results from using high-frequency stock return data.

long position in quintile 5 (high-climate-risk stocks) and the short position in quintile 1 (low-climate-risk stocks). Unlike other papers in the asset pricing literature that focus on deciles ("10-1" spread), our choice to split the data by quintile is motivated by the limited availability of climate data at the beginning of the sample. Thus, we ensure that no portfolio ever contains fewer than 80 stocks, with an average of 200 stocks per portfolio over the entire period. These figures are in line with existing factors in the literature, such as the liquidity factor of Pástor and Stambaugh (2003). To ensure proper portfolio diversification, we construct climate risk factors only at the European level. We recognize that these regional factors may not fully reflect local climate shocks in smaller European countries. On the other hand, such shocks are unlikely to affect the stability of the European financial system.

In the case of transition risk, the long and short positions are determined by their GHG emission intensity.[11] We use both reported and estimated emission intensities, Scopes 1 & 2, divided by net sales, from Refinitiv Datastream. We do not include Scope 3 because political authorities and consumers may consider that it is beyond the company's remit to reduce this type of emission. Given the extensive debate in the literature on the choice of carbon data and its effect on the estimation of the carbon premium, we test the robustness of our results to alternative specifications of the transition risk factor using unscaled GHG emissions (in line with Bolton and Kacperczyk, 2021), lagged emission intensities (as per Zhang, 2024), and reported GHG emission intensities only (as per Aswani et al., 2024). We also calculate the

[11] As Giglio et al. (2021) point out, measuring transition risk using GHG emission intensities is the most common approach in the literature, although there are other possibilities (e.g. using unscaled emissions; Bolton and Kacperczyk, 2021). Aswani et al. (2024) argue that while unscaled emissions are an important measure for society, emission intensity is a more appropriate measure for assessing carbon performance at the level of individual companies. However, we recognize that while GHG emission intensities are likely to reflect risks arising from regulatory changes and consumer preferences, they may not reflect the risks of climate-related technological disruption.

returns of the long–short portfolio using deciles ('10-1' spread) instead of quintiles (see Appendix D).

To mitigate the correlation with existing factors, the transition risk factor is constructed using six value-weighted portfolios formed on market capitalization (B for "Big", S for "Small", see Equation 4), book-to-market (H for "High", L for "Low"), and the two lowest and highest deciles of GHG emission intensities (G for "Green", B for "Brown"). We disentangle "Big" and "Small" firms, as well as "High" and "Low" firms at date *t*, based on the median value of market capitalization and the book-to-market ratio at date *t*-1 in our sample.

$$BMG_t = \frac{LB_t + HB_t + SB_t + BB_t}{4} - \frac{LG_t + HG_t + SG_t + BG_t}{4} \tag{5}$$

where BMG, which stands for "brown-minus-green", represents the returns of the transition risk factor; LB, HB, SB, and BB are the returns of the brown portfolios; LG, HG, SG, and BG are the returns of the green portfolios; and *t* represents monthly observations. Even if GHG emission intensity data are updated at a yearly frequency, the portfolios are rebalanced monthly according to the previous month's value of the respective characteristics. In a given period, we include in the portfolios only those nonfinancial stocks for which the data for all characteristics are available. In 2005, data were available for approximately 400 European nonfinancial stocks compared with 2,070 in 2022. Our study starts in 2005 because there are not enough data available on GHG emission intensities before this date.

In the case of physical risk[12], we sort firms based on the physical scores provided by Trucost, which aggregates the scores of seven hazards (coldwave, flood, heatwave, hurricane, sea level rise, water stress, and wildfire). Specifically, we use the Composite Moderate 2050 score, which

[12] In contrast to GHG emissions in the case of transition risk, there is no raw indicator that consensually captures physical risk. Therefore, we rely on third-party physical risk ratings to construct our physical risk factor. We acknowledge that this may affect our findings on physical risk.

represents the exposure to physical risk at the 2050 horizon if climate change is moderate (Representative Concentration Pathway 4.5).[13] We also test the robustness of our results to alternative specifications of the physical risk factor using the physical scores provided by Carbon4Finance and ISS-ESG (see Appendix D).

In contrast with BMG, the correlation between the physical climate risk factor and the "value" factor (HML) is naturally low; thus, we filter portfolios only based on market capitalization. Therefore, the physical climate factor is built using four value-weighted portfolios formed on size (B for "Big", S for "Small") and the two lowest and highest deciles of Trucost physical scores (V for "Vulnerable", S for "Safe"):

$$VMS_t = \frac{SV_t + BV_t}{2} - \frac{SS_t + BS_t}{2} \tag{6}$$

where VMS stands for "vulnerable-minus-safe", the returns of the physical risk factor; SV and BV are the returns of the vulnerable portfolios; SS and BS are the returns of the safe portfolios; and *t* represents monthly observations. As with BMG, the allocation of VMS is rebalanced on a monthly basis; however, the physical scores are fixed over time.

In Appendix D, we analyze the capacity of factors to hedge against exogenous climate shocks. We also test whether these factors are reflected in the returns of nonfinancial stocks and conduct additional robustness and placebo tests.

Factor VaR

Our measure of systemic risk is derived from the VaR of the equity returns of financial institutions. For consistency, we estimate the VaR of the previously defined climate risk factors, BMG and VMS, according to the method described in Appendix C. The transformed factors,

[13] Using different scenarios, such as the Composite High 2050 score, does not change our results.

called ΔVaR_{BMG} and ΔVaR_{VMS}, reflect the dynamics of tail climate risks. They represent the estimated loss of a long–short portfolio that, within a given month, is not exceeded with a given probability. An increase in tail climate risk may result from a greater risk of correction in GHG-intensive stocks or an increase in the probability of outperformance in low emitters, which is likely to occur in the event of negative climate shocks (Ardia et al., 2022; Pástor et al., 2021). The VaR measure is derived from the volatility of returns, a key aspect of capturing the degree of uncertainty in the pricing of green and brown stocks. This ex ante vulnerability approach is appealing given the difficulty in predicting the effect of climate risks on future corporate cash flows due to model limitations, environmental tipping points, potential disruptions in green technologies, and uncertain policy responses (e.g., Barnett et al., 2020; Weitzman, 2009). In Appendix C, we show that our main results are robust to different models and error distribution assumptions for estimating the VaR.

2.3. Climate risk and financial stability

We examine a financial system comprising N financial institutions and propose two tests to evaluate the contagion effects induced by climate risks in the financial sector, encompassing common exposures, spillovers, and pure contagion (Masson, 1998). First, we perform a time series regression of the common variation in tail risk among financial institutions onto our climate risk factors. Second, we introduce a two-stage regression framework to assess whether the financial institutions that are more exposed to climate risks contribute more to systemic risk.

Time series regression

We propose a time series regression to assess whether climate-related shocks induce comovements in tail risk across institutions. Specifically, we assume a reduced-form factor structure for the variations in systemic risk $\Omega_{1,t}$, estimated in Equation (3), such that $\Omega_{1,t}$ satisfies the following linear factor model:

$$\Omega_{1,t} = \alpha + \delta_f f_t + \delta_g g_t + \varepsilon_t \quad (7)$$

f is a set of climate risk factors that we proxy using $\Delta VaR_{BMG,t}$ and $\Delta VaR_{VMS,t}$, the tail transition and physical climate risk factors, constructed in Section 2.2. The factor set g contains control variables that may drive the variations in extreme risk in the European financial sector. We include a comprehensive set of macroeconomic and financial variables that reflect the degree of risk aversion in the euro area, namely, the liquidity of the interbank market, the default premium, and the state of economic activity. This approach, akin to an aggregate (systemic) risk factor estimation, evaluates the effect of climate risks on simultaneous changes in the downside risk of financial institutions. We consider that climate risks exacerbate tail dependence among financial institutions if the coefficient δ_f is positive and significant. The error term ε_t is subject to $\mathrm{E}[\varepsilon_t|\Psi_{t-1}] = 0$ and $\mathrm{Cov}\left[\varepsilon_t, f_{i,t}\middle|\Psi_{t-1}\right] = 0$, where Ψ_{t-1} is the lagged information set.

Two-stage regression framework

The first stage involves estimating *N* time series regressions to assess the sensitivity of each financial institution's extreme risk (measured by changes in the VaR) to tail climate risks:

$$\Delta VaR_{i,t} = \alpha_i + \beta_{i,f} f_t + \beta_{i,g} g_t + \varepsilon_{i,t} \quad (8)$$

$\Delta VaR_{i,t}$ represents the estimated variations in extreme risk for each financial institution *i* in period *t* (see Appendix C), and f and g are the previously defined sets of climate, macroeconomic, and financial factors. The same assumption applies to the error terms (see Equation 7). The coefficient $\beta_{i,f}$ analyzes the contribution of the tail climate risks to each financial institution's stress (first-round effects).

The second stage assesses whether institutions that are more sensitive to climate risks contribute more to systemic risk through tail comovements (second-round effects). The coefficients estimated in the first stage are used as independent variables in a cross-sectional regression:

$$\mathrm{X}_{1,i} = \alpha + \gamma_f \hat{\beta}_{f,i} + \gamma_g \hat{\beta}_{g,i} + \varepsilon_i \tag{9}$$

Equation (9) performs a cross-sectional OLS regression of X_1, the loadings of financial institutions to our systemic risk indicator Ω_1 (see Equation 3), onto $\hat{\beta}$ estimated in Equation (8), which represents individual exposures to climate and control risk factors. A positive and significant γ_f indicates that institutions with greater climate risk exposure exhibit stronger tail dependence on the financial system, exacerbating systemic risk. This test and the choice of independent variables stem from the fact that the covariance across ΔVaR_i, denoted as $\sum$, is determined by the following relation (after suppressing time subscripts):

$$\sum = \beta_f \beta_f' var(f) + \beta_g \beta_g' var(g) + \left(\beta_g \beta_f' + \beta_f \beta_g'\right) cov(f,g) + \mathrm{E}[\varepsilon\varepsilon'] \tag{10}$$

where β_f and β_g are matrices containing the individual coefficients estimated in Equation (8). Empirically, we find that our model captures 80% of the correlation between changes in the tail risk of financial institutions.

Climate exposure CoVaR indicator

The methodology described above can be adapted to construct climate risk indicators that distinguish between first- and second-round effects of transition and physical risks on the financial sector. These climate exposure CoVaR indicators (C-CoVaR) allow policymakers and stakeholders to quantify potential financial losses and monitor climate risk dynamics over time. This approach leverages quantile regressions, which also provide a robustness check for the main results of the paper. The approach is detailed in Appendix E, and the results are described in Section 3.2.

2.4. Estimation methods

Time series regression

We estimate Equation (7) over the entire period from 2005 to 2022 because of the moderate size of the time series (207 monthly observations). We use two standard error estimation methods for this time series regression. Since diagnostic tests indicate the presence of autocorrelation and heteroscedasticity in the residuals, we report robust standard errors based on Newey and West (1987). Moreover, to address the issue of nonnormally distributed errors and the moderate sample size, we estimate the model nonparametrically based on a bootstrapping approach.[14] More specifically, we resample the data with replacement, generate 10,000 bootstrap replicates of the regression coefficients, and calculate the bias-corrected and accelerated 90% confidence intervals. Finally, to capture the possibility that the impact of climate risks on systemic risk has increased over time, we estimate Equation (7) using an exponentially weighted scheme with a decay factor of 0.98, which assigns greater weight to more recent observations.

First-stage regression

For the first stage (Equation 8), we first run separate standard OLS regressions for each financial institution over the entire period from 2005 to 2022. This step allows us to estimate

[14] Because it does not require distribution assumptions, bootstrapping can produce more accurate inferences when data do not conform to the assumption of normality or when the sample size is small.

the sensitivity of the VaR of each institution to tail climate risks. We then use these coefficients as independent variables in the second-stage regression (Equation 9).

Additionally, we exploit macro panel data to propose a dynamic estimation of the climate risk exposures. Specifically, we use the mean-group (MG) estimator (Pesaran and Smith, 1995), which accounts for cross-sectional heterogeneity. We run the *N* regressions dynamically based on a rolling window of 100 monthly observations. Next, we aggregate individual coefficients and compute standard errors. Following Pesaran and Smith (1995), the MG coefficients and their asymptotic variance are consistently estimated as follows:

$$\hat{\beta}_{MG,t} = \frac{1}{N}\sum_{i=1}^{N}\hat{\beta}_{i,t} \tag{11}$$

$$\hat{\sigma}^2_{\hat{\beta}_{MG,t}} = \frac{1}{N(N-1)}\sum_{i=1}^{N}(\hat{\beta}_{i,t} - \hat{\beta}_{MG,t})(\hat{\beta}_{i,t} - \hat{\beta}_{MG,t})' \tag{12}$$

where $\hat{\beta}_{i,t}$ is the exposure of financial institution *i* to either transition or physical risk at time *t*. To mitigate the risk that errors in individual estimates from Equation (8) bias the MG coefficients in Equations (11) and (12), we compute the mean using a robust regression of individual estimates on a single cross-sectional unit. One advantage of the MG estimator is that it is robust to coefficient heterogeneity, allowing us to derive the average exposure to tail climate risks by industry type and country and to compute the respective confidence intervals.

Second-stage regression

Regarding the cross-sectional regression (Equation 9), we report robust standard errors based on White (1980). Then, we estimate the regression with fixed effects for industries and countries and clustered standard errors. Moreover, we estimate the model nonparametrically based on the bootstrapping approach described above.

This second-stage regression uses the factor coefficients from Equation (8), which may contain estimation errors, as regressors. To attenuate the inherent errors-in-variables (EIV) bias, we employ the following two approaches. First, we use the Bayesian shrinkage factor of Vasicek (1973), which suggests shrinking each individual estimate toward a prior, depending on the relative precision of the individual coefficient ($\hat{\beta}_i$) and prior ($\hat{\beta}_{sect}$). We obtain a posterior belief of the estimator ($\hat{\beta}_i^{Shr}$) following Equation (13):

$$\hat{\beta}_i^{Shr} = \frac{\sigma_{\beta_{sect}}^2}{\sigma_{\beta_i}^2 + \sigma_{\beta_{sect}}^2}\hat{\beta}_i + \frac{\sigma_{\beta_i}^2}{\sigma_{\beta_i}^2 + \sigma_{\beta_{sect}}^2}\hat{\beta}_{sect} \tag{13}$$

where $\sigma_{\beta_i}^2$ and $\sigma_{\beta_{sect}}^2$ are the variances of the coefficients $\hat{\beta}_i$ and $\hat{\beta}_{sect}$, respectively. Following Karolyi (1992), we use a specific (informative) prior for each sector–factor pair. Each prior ($\hat{\beta}_{sect}$) is computed as the cross-sectional average of all individual estimates associated with a given sector and risk factor. Consequently, when the variance of the estimator is high compared with that of the respective prior, the individual coefficient is strongly adjusted toward the prior.

Second, we use the instrumental variable (IV) approach proposed by Jegadeesh et al. (2019). On the basis of their method, we first estimate individual coefficients from Equation (8) from a random subset representing half of the observations in the data sample. These betas are considered the “explanatory” variables for the second-stage regression (Equation 9). We then reestimate the individual coefficients (Equation 8) using the other half of the data sample, and these betas are the “instrumental” variables. Since we estimate the explanatory and instrumental variables from disjoint data samples, their measurement errors are not cross-correlated. Overall, this IV approach shrinks the individual coefficients used as explanatory variables toward the cross-sectional means of their instruments.

2.5. Data

Stock market data

We collect monthly stock market data from 2005 to 2022. We use equity data instead of bond or CDS data for reasons of availability and consistency with the other stages of the framework. From Refinitiv Datastream, we obtain an initial list of 21,788 European stocks—8,750 active and 13,038 dead (as of 2022)—including members of the European Union, Norway, Switzerland, and the United Kingdom (UK). We use common equities only, thus excluding preference shares, warrants, closed-end funds, and European depositary receipts. In addition, we focus on the primary market in the case of multiple listings. Following Landis and Skouras (2021), we clean the data by searching for specific strings in the name of the companies ("Full name" Datastream variable) to eliminate assets that may have been misclassified as stocks by Datastream. Through this procedure, we remove 1,713 assets from the initial database.

Based on the remaining list, we download the prices (including dividends) and compute the log returns from the available price series (15,786).[15] We apply several filters recommended by Landis and Skouras (2021) to address implausible returns, illiquidity, and unusually high or low volatility. Specifically, we eliminate from our sample the series for which more than 95% of the returns have the same sign (positive or negative). We then discard the series for which more than 25% of the returns equal zero, as this is a sign of illiquidity. Finally, we eliminate stocks for which the monthly standard deviation of returns is greater than 40% or less than 0.01%. The remaining database contains 12,283 shares, including 9,958 nonfinancial assets. We use

[15] For prices, we use the following function on Datastream ("DPL#(X(RI)~E,9)"), which allows us to obtain enough decimal digits to avoid confusing small returns with illiquidity.

nonfinancial assets to construct the climate risk factors, whereas financial stocks serve as the input to our systemic risk measure.

Financial institutions

We select financial institutions according to the FTSE/DJ Industry Classification Benchmark (banks, life insurance, nonlife insurance, financial services, real estate investment and services, and real estate investment trusts).[16] Like other studies (see, e.g., Acharya et al., 2017; Engle et al., 2015), we focus on large financial institutions, as they are the primary sources of systemic risk. More precisely, we include all active financial institutions in Europe with a market capitalization greater than 100 million euros on average from 2005 to 2022. Our final sample consists of 371 financial institutions, including 127 banks, 10 life insurance companies, 28 nonlife insurance companies, 111 financial services companies, 71 real estate investment and services firms (REISs), and 24 real estate investment trusts (REITs). The ten most represented countries are the UK (55), Switzerland (49), France (37), Germany (33), Sweden (27), Italy (25), Belgium (20), Norway (19), Denmark (18), and Poland (18). Table A.1 presents the descriptive statistics of the 371 European financial institutions included in our sample. The average market capitalization of our institutions is €635 million, with a net income-to-total assets ratio of 0.023, a market-to-book ratio of 1.28, a market beta of 0.82, and a debt-to-equity ratio of 45.9%. A list of the largest financial institutions in our sample is available in Table B.4.

[16] Financial services companies include financial and commodity market operators, investment fund managers, and brokerage services. Real estate investments and services comprise the rental, development, and operation of real estate assets.

Financial and environmental variables

We collect a large set of financial and environmental variables from multiple sources for our sample of shares (see the list, definitions, and data sources in Tables B.1 and B.2). We retrieve financial characteristics, including market capitalizations, book values of equity, cash holdings, total assets, incomes, net sales, and fixed assets in euros, from Refinitiv Datastream. The institution-level environmental variables are from several sources, namely, Refinitiv Datastream, Trucost, ISS-ESG, Carbon4Finance, CDP, and Bloomberg. To study the institutional ownership structure of European financial institutions, we use Securities Holdings Statistics, a unique proprietary dataset of the Eurosystem. Finally, we collect country-level environmental variables from various other sources (see Table B.3).

Economic and financial risk indicators

We use a collection of macroeconomic and financial variables that might drive the level of systemic risk in the financial sector as controls in the regressions (Equations 7 and 8). Indeed, changes in macroeconomic and financial risk can help explain variations in the equity risk premium (e.g., Lettau et al., 2008) and are significant determinants of systemic risk (e.g., Adrian and Brunnermeier, 2016). We download the excess returns of the European market (MKT) from Kenneth French's website and the risk reversal (RR) on the USD/EUR options from Bloomberg, for which a negative value implies that expectations are skewed toward the depreciation of the euro. We then build a series of fixed-income spreads. The 3-month Euribor rate against the OIS represents interbank market liquidity (IM). The 10-year against the 2-year euro area interest rates capture the slope of the yield curve (YC). The 10-year German sovereign bond rate against an average of 10-year rates in Greece, Ireland, Italy, Spain, and Portugal reflects the divergence in rates between countries in the North and South of the euro area (NS).

The high-yield euro corporate rates against the 3-month Euribor rate represent the default premium (DP). Finally, we use an economic sentiment (ES) indicator based on surveys from Eurostat. For consistency with the dependent variable in Equations (7) and (8), we estimate the VaR of the financial risk indicators. Although this choice is debatable, we find that using the VaR of the independent variables compared with the unfiltered data leads to a substantial increase in the model's adjusted R-squared. We make an exception for risk reversal because it is an option-based measure for which the price is already derived from the volatility of the underlying assets. Moreover, we do not estimate the VaR of the economic sentiment, as the procedure does not seem appropriate for an indicator that is not based on market data. We control for multicollinearity between the explanatory variables using the variance inflation factor (VIF). We find that the explanatory variables have a VIF of 1.8 on average, with the highest VIFs for ΔVaR_{DP} and ΔVaR_{MKT} (3.7 and 3.2, respectively).

Systematic risk factors

Since our systemic risk measure is derived from equity market data, we also incorporate a selection of systematic risk factors as alternative control variables. These variables help explain risk and returns in the equity market (see Harvey et al., 2016). First, we use the European Fama and French (2015) and Carhart (1997) factors. These factors include the small-minus-big factor (SMB) based on market capitalization, the high-minus-low factor (HML) based on book-to-market, the robust-minus-weak factor (RMW) based on profitability, and the conservative-minus-aggressive factor (CMA) based on investment. Carhart (1997) also proposes the winner-minus-loser factor (WML), which captures a momentum effect. Alternatively, we also use the *q5* factors of Hou et al. (2015, 2021), the nontraded version of the liquidity factor (LIQ) of Pástor and Stambaugh (2003), and the quality-minus-junk (*QMJ*) factor of Asness et al. (2019).

The *q5* factors include the market excess returns, the size factor (*ME*), the investment factor (*IA*), the return on equity factor (*ROE*), and the expected growth factor (*EG*).[17]

Although the economic content of these factors is unsettled (Kozak et al., 2018)[18], Ang (2014) notes that "each factor defines a different set of bad times." For example, Smith and Timmermann (2022) identify breaks in risk premia during crisis periods. For consistency with the dependent variable, we estimate the VaR of these systematic risk factors. This procedure seems well suited for a focus on the occurrence of bad events, such as distress in small and value stocks (Fama and French, 1995) or momentum crashes (Daniel and Moskowitz, 2016). It also leads to a substantial increase in the model's adjusted R-squared compared with the use of unfiltered data. Table A.2 reports limited correlation across the estimated ΔVaR of all factors, indicating that they reflect nonoverlapping information that can help explain the variations in systemic risk in the financial sector. ΔVaR_{BMG} is slightly correlated with ΔVaR_{WML}, ΔVaR_{CMA}, and ΔVaR_{HML} at 21%, 19%, and -22%, respectively. ΔVaR_{VMS} is moderately correlated with ΔVaR_{WML}, ΔVaR_{DP} (the default premium) and ΔVaR_{MKT} at 26%, 26% and 25%, respectively. The correlation coefficient between ΔVaR_{BMG} and ΔVaR_{VMS} is -5%.

3. Empirical results

3.1. Individual exposures of financial institutions to tail climate risks

In this section, we examine the individual effect of climate risks on financial institutions estimated via Equation (8). First, we provide details on the distribution of individual risk exposures by sector and country. Notably, the high climate risk exposure of some groups of

[17] We download Fama and French factors from Kenneth French's website, the q5 factors from the data library at global-q.org, the liquidity factor from Robert Stambaugh's website, and the QMJ factor from AQR Capital's website.

[18] Whereas the asset pricing theory states that factor returns are compensation for risk, they can also emerge due to behavioral biases or institutional and informational frictions.

financial institutions may have dual origins: acute climate risks, in terms of regulation or natural disasters, or a degraded balance sheet (or other characteristics), which makes institutions more vulnerable to climate shocks.[19] Second, we examine the dynamic exposure of financial institutions to climate risks to determine whether exposure to risk has increased over time. Third, we run a variance decomposition of individual exposures to tail climate risks to better understand the sources of variations in our measure, both in time series and cross-sectional dimensions.

Static estimation

Figure A.3 shows the distribution of the exposure to transition and physical risks of financial institutions estimated via Equation (8). We observe that the distribution of exposure to transition risk is skewed to the right, indicating that a larger proportion of financial institutions have high transition risk. This positive skewness appears to hold for all types of financial institutions except for REISs. This is particularly noticeable for REITs and life insurance, which might be due to the long-term nature of these activities. This skewness also occurs in most European countries, although it is most pronounced in Denmark, Finland, France, Ireland, Romania, Sweden, and the UK (see Figure A.4).

In contrast, financial institutions' exposures to physical risk have a more balanced distribution, albeit with a slight leftward skew, suggesting that investors do not generally evaluate physical hazards as a tail risk for financial institutions. The negative coefficients can be explained by the fact that some financial institutions face increased demand after natural disasters (e.g., Cortés and Strahan, 2017; Shelor et al., 1992). This leftward skew is visible for

[19] We study the characteristics that interact with individual climate risk exposures in Sections 3.3 and 3.4.

all types of financial institutions (see Figure A.3). Nevertheless, a few Eastern European countries are exceptions: Greece, Romania, Hungary, and Lithuania (see Figure A.4).

Dynamic estimation

We now explore the dynamics of financial institutions' exposure to climate risks via Equation (8). The results show that financial institutions' exposure to transition and physical risks has increased over the past decade (see Figure A.5, Panels A and B), primarily after the Paris Agreement in December 2015. Nevertheless, only the exposure to transition risk appears positive and significant over the entire period.

Focusing our attention on specific sectors (see Figure A.6), we show that exposure to transition risk has mostly increased for banks and life and nonlife insurance companies, with the MG coefficient becoming significant after 2015–2017. Our results differ from those of the contemporaneous paper of Jung et al. (2025), which focuses on banks and does not find an upward trend in their exposure to climate risk. This discrepancy may be explained by the fact that we focus on extreme climate risk and use a transition risk factor that includes many firms, whereas their factor is centered on coal and oil companies. The upward trend is less clear for financial services firms; however, we still observe that exposure to transition risk became significant after 2017. For real estate companies, no trend is discernible, but REITs' exposure to transition risk is positive and significant over the entire period, which is consistent with the results of the static estimates. With respect to physical risk (see Figure A.7), none of the financial industries show significant positive exposure; however, there is still an upward trend, with the coefficient for most industries becoming nonsignificantly positive by the end of the period, except for REISs.

Next, we examine the dynamics of exposure to climate risks in the countries most represented in our sample of financial institutions. Regarding transition risk, we observe upward trends in France, Germany, Italy, Norway, and the UK, although the coefficients are not significantly positive at the end of the period in Germany and Italy (see Figure A.8). With respect to physical risk, we observe positive trends in France, Italy, Norway, and the UK (see Figure A.9). However, only in Norway and the UK are the coefficients positive and significant in 2022. These results indicate considerable heterogeneity in exposure to climate risks at the country level.

Variance decomposition of tail climate risk exposures

To obtain a better understanding of the sources of the variation in individual climate risk exposures, we conduct a variance decomposition, as shown in Table A.3. More precisely, we regress our indicators on a set of fixed effects. By adding one type of fixed effect at a time, we can gauge the incremental explanatory power of a given type of fixed effect.

We start with transition risk in column (1). We find that year fixed effects explain 1.43% of the variation in transition risk exposures. The additional explanatory power of sector (country) fixed effects is 2.33% (6.60%). Then, sector-year and country-year fixed effects are added. They contribute to explaining an additional 0.63% and 6.35% of the variance, respectively. Finally, institution fixed effects capture 38.6% of the variance. After all of these fixed effects are included, 56.0% of the variation is explained. The importance of the country and country-year dimensions could be mechanically due to the presence of countries with few financial institutions. In column (2), we restrict our analysis to countries with more than 100 institution-year observations and still find that country and country-year fixed effects have comparatively more explanatory power than sector and sector-year fixed effects.

We then focus on physical risk in column (3). Our results indicate that institution fixed effects incrementally explain 36.7% of the variation in exposure to physical risk, whereas country and country-year fixed effects account for 10.8% and 10.1%, respectively. Altogether, the fixed effects explain 61.1% of the variation in individual physical risk exposure. After the sample is restricted to countries with more than 100 observations, the results are qualitatively similar; see column (4).

Overall, fixed effects explain 53.5% to 61.1% of the variation in exposure to climate risks. Institution, country, and country–year fixed effects have superior explanatory power compared with year, sector, and sector–year fixed effects. Country fixed effects are especially important in explaining changes in exposure to physical risk. Finally, a significant part of the variation occurs at the institution-year level and, therefore, cannot be captured by fixed effects.

3.2. The effect of tail climate risks on systemic risk

In this section, we focus on the second-round effect of extreme climate risks on the European financial sector. In contrast to Section 3.1, in which we analyze individual financial institutions' exposure to climate risks, we assess whether climate risks are associated with extreme risk dependence among financial institutions, considering the potential contagion effects in the financial sector that may arise from climate risks.

Time series regression

Using time series regressions (Equation 7), we examine in Table A.4 whether climate risks significantly contribute to tail risk dependence among financial institutions after several factors known to be predictors of systemic risk are considered. We run regressions of Ω_1, our indicator of systemic risk capturing common time variations in the VaR of financial institutions, on tail climate risk factors (BMG for transition risk and VMS for physical risk). Overall, we observe a positive and significant impact of transition risk on systemic risk, whereas physical risk has no significant effect. We find that a one standard deviation increase in the VaR of the transition risk factor leads to an increase of approximately 0.06 standard deviation in systemic risk (baseline specification).[20] These results are robust when we control for SMB and HML factors (column 2), when we further include RMW, CMA, and WML (columns 3 and 4), and when all regressors are included together (column 5). In addition to transition risk, we find that MKT, DP, ES, SMB, HML, and WML are positively and significantly linked to systemic risk in the European financial sector. The adjusted R-squared of our specifications is between 0.81 and 0.89, which suggests that the potential biases related to the presence of omitted variables are limited.

Alternatively, in Table OA.2 (Online Appendix), we replace the Fama and French factors with the *q5* factors of Hou et al. (2015) and add the *LIQ* and *QMJ* factors to the list of controls.[21] We also include Brent returns to check that BMG's effect on systemic risk does not stem from oil shocks. With this alternative set of factors, we confirm that the effect of transition risk on systemic risk is significant at the 10% level for all specifications. In addition to transition risk, we find that MKT, DP, ES, EG, and LIQ are positively and significantly associated with systemic risk. The results are also robust to alternative specifications of the climate risk factors, detailed in Appendix D, and other estimation methods (see Table OA.3). Finally, in Table OA.4, we estimate Equation (7) using an exponentially weighted scheme with a decay factor of 0.98, which assigns greater weight to more recent observations. We observe a stronger effect of

[20] This magnitude is comparable, for instance, to Anginer et al. (2014), who find that a one standard deviation decrease in competition increases systemic risk by 0.12 standard deviation, or to DeYoung and Huang (2021), who report a 0.04 to 0.09 increase in systemic risk when the risk sensitivity of bank CEOs' pay increases by one standard deviation.
[21] The analysis period is slightly shorter, as these factors are available only until the end of 2021.

transition risk on systemic risk, with coefficients ranging from 0.07 to 0.17. This finding aligns with the notion that policies supporting the transition to a low-carbon economy have become increasingly stringent, coupled with growing investor awareness of the future risks these policies may pose to financial institutions.

Overall, our results indicate that transition risk impacts systemic risk in the time series. In contrast, physical risk does not seem to be priced as a systemic risk factor. This disparity may be attributed to the limited synchronicity of natural disasters on a European scale, whereas transition shocks are more likely to affect many companies simultaneously (e.g., Bolton and Kacperczyk, 2021). Finally, the divergence in physical risk scores among different data providers may disperse investment flows in the event of a natural disaster, limiting or delaying the incorporation of physical risk into asset prices (e.g., Billio et al., 2021 for ESG scores).

Two-stage regression framework

Next, we conduct a cross-sectional analysis in Table A.5 to check whether the financial institutions most exposed to climate risks (according to the values of $\hat{\beta}_{BMG}$ and $\hat{\beta}_{VMS}$) contribute more to the tail dependence in the financial sector (X_1) after controlling for the exposures to other risk factors. We find positive and significant coefficients associated with exposure to transition risk, whereas exposure to physical risk does not seem to affect financial institutions' contribution to global risk.

We start by reporting our results with heteroskedasticity-robust standard errors (columns 1 to 4). We then verify that our findings are robust to the inclusion of fixed effects for the country and financial industry, as well as for standard errors clustered at the country level (columns 5 to 8). Including fixed effects allows us to test whether climate risks also contribute to global downside risk in each financial industry and country. Apart from transition risk, we also show that exposure to MKT, DP, ES, SMB, HML, and ML tends to be positively linked to the contribution of financial institutions to systemic risk. We report adjusted R-squared values between 0.13 and 0.41. Interestingly, some differences emerge between the results based on the time series and the cross-sectional regressions, as illustrated by the effect of ML, the interbank market liquidity indicator, which appears significant only in the cross-sectional regressions. This discrepancy indicates that the two-pass regression procedure is useful for ensuring the robustness of the results.

Based on an alternative set of factors, we confirm in Table OA.5 (Online Appendix) that among climate risks, only exposure to transition risk appears to have a consistently positive and significant effect on the contribution to systemic risk (columns 1 to 5). In contrast, the coefficients associated with physical risk do not exhibit a consistent pattern. In addition, we find positive and significant effects associated with exposure to MKT, ME, ROE, EG, LIQ, QMJ, and YC. The conclusion remains unchanged when we estimate standard errors using a bootstrapping approach (see Table OA.6) and when we use two approaches for mitigating EIV bias (see Tables OA.7 and OA.8). Finally, in Table OA.9, we use the average correlation of each financial institution's tail risk with the remaining financial system—capturing the information contained in all principal components—as the dependent variable in Equation (9). This alternative specification confirms our previous results. Overall, our findings indicate that transition risk positively and significantly contributes to systemic risk, both in the time series and cross-sectional dimensions. In contrast, physical risk does not yet seem to have an impact on systemic risk.

Climate exposure CoVaR indicator

In Appendix E, we explain how our methodology can be used to derive climate risk indicators. We find that the C-CoVaR related to transition risk exhibits distinct dynamics over the period analyzed (Figure E.1). Between 2010 and 2016, the indicator was positive and driven primarily by first-round effects, with an increase in the daily VaR conditional on a transition climate shock ranging between 0 and 5 billion euros.[22] This suggests that only a subset of the financial sector was significantly exposed to transition shocks during this period, thereby limiting the scale of contagion effects. At the end of 2016, C-CoVaR became negative, coinciding with the election of Donald Trump, signaling a potential shift in market expectations or policies related to climate transition risk. The indicator began to rise again in 2019, reaching a peak in 2022 at an estimated 15 billion euros at risk. In the latter half of the period, the second-round effects of transition risk on the financial sector became dominant. This shift likely reflects increasing similarities in transition risk exposures across the financial sector (i.e., systemic as a herd) and the amplification of risks through spillovers or pure contagion effects.

Regarding the physical risk indicator, we find that the European financial sector, on average, exhibits positive but limited exposure to physical shocks, with an increase in the daily VaR rarely exceeding 2.5 billion euros (Figure E.2). The indicator is driven predominantly by first-round effects, reflecting the uneven exposure of financial institutions to such shocks. However, the indicator peaked at an extremum of 7 billion euros at the beginning of 2018, a spike that may be associated with a series of severe winter storms across Europe during this period. Overall, this analysis confirms that financial institutions were not significantly exposed to physical risk during the period 2010–2022. Furthermore, the magnitude of second-round effects associated with physical risk remains limited.

[22] The magnitude of this effect depends largely on the size of the shock under consideration. We focus here on a climate shock that is likely to occur once a month. Considering a more extreme climate shock can dramatically increase the assessment of potential climate-related financial losses.

3.3. Individual characteristics of financial institutions and tail climate risks

In this section, we investigate the institution-level characteristics associated with exposure to tail climate risks. We report our results in Table A.6 for the case of transition risk. We start by regressing individual (statically estimated) exposures to transition risk (see Equation 6) on the natural logarithm of market capitalization, net income, market-to-book, cash, debt, and equity market beta. Our results, reported in column (1), indicate that market capitalization, profitability, debt, and the equity beta are positively associated with individual exposure to transition risk. This finding is consistent with the climate risk stress test of the European Central Bank, which shows that large institutions tend to be more exposed to the sectors with the highest emissions.[23] In contrast, tail transition risk is negatively correlated with cash levels, suggesting that high-exposure institutions may have less liquidity to address the effects of climate shocks on portfolios. We then confirm these results in column (2) after including country and industry fixed effects. We use the dynamically estimated transition risk exposure coefficients as the dependent variable in column (3), allowing us to include year fixed effects. Our results confirm that larger and more indebted financial institutions tend to have greater exposure to transition risk than do other financial institutions.

Next, we augment our regressions with additional extrafinancial characteristics and assess their association with transition risk exposure. We first investigate the impact of Scope 3 GHG emissions (GHG emissions indirectly emitted by financial institutions, primarily through their investment and loan portfolios). We find that having very low Scope 3 emissions is negatively

[23] In July 2022, the European Central Bank (ECB) released the results of its climate risk stress test, conducted on a sample of 41 large banks. Consistent with our finding of a positive association between financial institutions' market capitalization and their exposure to transition risk, the ECB states that *"the most emitting sectors […] tend to be dominated by large companies (proxied by the size of revenues) which may be more likely to enter into relationships with larger banks."* See here.

associated with exposure to transition risk (column 4).[24] After controlling for year- and institution-level fixed effects, we also find that exposure to tail transition risk is lower for institutions with third-party verified Scope 3 emissions (column 5) and for those reaching their emission reduction targets (column 6). Taken together, the results reported in columns 4 to 6 indicate that financial institutions with cleaner credit and market portfolios are less exposed to transition climate risk. They also suggest that both information reliability and emission reduction trajectories are considered in investors' risk assessments. In column (7), we investigate the relationship between the long-term incentives given to board members and transition risk. We find that exposure to transition risk is significantly lower when board members have long-term incentives, which indicates that long-termism can help reduce transition risk.[25] Next, we assess the association between transition risk and financial institutions' ownership structures. We find that financial institutions with higher institutional ownership have less exposure to transition risk (column 8). This result may be explained by the fact that institutional investors tend to have long-term portfolios. Moreover, institutional owners' long-term considerations may increase awareness of long-term issues such as climate risks among investee companies (see Dyck et al., 2019 and Chen et al., 2020 in the case of CSR activities).

In Table A.7, we examine which institution-level characteristics correlate with greater exposure to physical risk. We find that financial institutions with greater exposure to physical risk have lower market capitalizations and higher equity betas (columns 1 to 3). Thus, small

[24] The Scope 3 data we use is static. Hence, we do not use institution fixed effects here. In unreported tests, we define our dummy variable as equal to one if the Scope 3 emissions are in the bottom quartile (instead of the bottom 10%). The results are qualitatively similar but insignificant.

[25] These results are related to the findings of the climate stress test conducted by the ECB (see here). The ECB indicates that many financial institutions should improve their governance to increase their resilience to climate risks (see in particular Chart 4), and that *"most banks still do not have clearly specified long-term strategies for dealing with the green transition."*

financial institutions appear to be more exposed to physical risk, which can be explained by a lesser geographical diversification of their assets than that of large institutions. Physical risk also tends to be lower for institutions giving long-term incentives to board members and executives (column 4) and with higher institutional ownership (column 5), but these effects are statistically nonsignificant.

Overall, these findings suggest that the characteristics of financial institutions exposed to tail transition risk are different from those of institutions exposed to physical risk. Financial institutions tend to be less exposed to transition risk when they have a cleaner portfolio and higher institutional ownership and when they are committed to addressing long-term issues.

3.4. Country-level characteristics and tail climate risks

In Section 3.1, we highlight that the variance in our measure of climate risk exposure is explained primarily by firm- and country-level factors. After investigating the correlations between firm-level characteristics and our individual climate risk coefficients in Section 3.3, we focus on country-level characteristics and regulatory shocks in this section.

Country-level climate risk

We start by assessing the extent to which our institution-level coefficients are correlated with country-level climate risk measures. In Table A.8, we use several proxies of country-level transition risk. We leverage data from Our World in Data (University of Oxford) and the OECD data platform (Organization for Economic Cooperation and Development). We find that exposure to transition risk is lower for institutions from countries with higher renewable energy usage (column 1), low greenhouse gas emissions (column 2), and low greenhouse gas emissions per capita (column 3). In addition, transition risk is positively correlated with the natural logarithm of country-level greenhouse gas emissions (column 4). Next, in Table A.9, we redo this exercise for physical risk, using country-level indicators of physical climate risk from the Notre Dame Global Adaptation Initiative (ND-GAIN). Our results indicate that, all else being equal, exposure to physical risk is heightened for institutions from countries with high flood risk caused by climate change (column 1), high adverse impacts of climate change on life expectancy (column 2), and a stronger dependency on foreign countries for water resources (column 3).[26] Furthermore, in Table OA.10, we perform the same analysis for two subsamples: financial institutions with a share of international business above and below the median. Intuitively, institutions with a strong national bias (low percentage of international activities) should be affected by their home country's climate characteristics, whereas the impact may be limited for institutions with little home bias. Focusing on institutions with strong home bias, we find that increased country-level risks of floods (column 2), climate-induced life expectancy decreases (column 4), and water dependency (column 6) are associated with increased exposure to physical risk. Focusing on institutions with little home bias, we find that only country-level flood risk (column 1) is associated with greater exposure to physical risk.

Country-level regulatory shocks: ESG disclosure mandates

We now turn to country-level regulatory shocks. In Table A.10, we build on the ESG disclosure mandates implemented in various countries to carry out a staggered difference-in-differences estimation. To that end, we introduce the variable $ESGmandate$, a dummy variable equal to one after the adoption of an ESG mandate in the institution's country and zero otherwise. We rely on the list of ESG disclosure mandates compiled by Krueger et al. (2021).

[26] The construction of our physical risk factor relies on the aggregate physical risk scores provided by Trucost. These aggregate scores consider several hazards related to water, see here. This could explain the sensitivity of our tail physical risk indicator to water-related risks.

Our institution-level climate risk exposures reflect investors' assessment of tail climate risks. Since ESG disclosure mandates can increase the availability of climate-related information, we expect that our transition risk coefficients may be sensitive to the implementation of such mandates. We do not have strong priors on the direction of the effect: in aggregate, the additional information becoming available after the ESG mandate could lead investors to revise their risk assessment upward or downward. In column (1), we find that the implementation of ESG mandates has a negative but insignificant effect on institutions' exposure to transition risk after controlling for country, industry, and year fixed effects.[27] We then decompose the sample into two subsamples on the basis of the median value of the exposure to transition risk. When decomposing, we find that ESG mandates decrease the transition risk of institutions with above-median exposure (column 2) but have no effect on institutions with below-median initial exposure (column 3). The difference between the coefficients in the two subsamples is statistically significant at the 1% level. Adding institution fixed effects yields qualitatively similar results (columns 4 to 6). This suggests that increased transparency can help the most exposed institutions reduce their transition risk.

Overall, we uncover a link between individual climate risk exposures and prominent regulatory shocks occurring during our sample period. Our approach leverages arguably exogenous shocks and includes a wide array of control variables and fixed effects. However, we should remain cautious about making causal claims, as other factors, notably country-level trends, may act as confounders. Rather, the results of this section should be taken as suggestive evidence of the impact of regulatory shocks on climate risk mitigation, as well as additional validation exercises of our individual climate risk measures.

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[27] Country fixed effects allow us to control for any time-invariant difference between countries choosing to implement ESG disclosure mandates (treated group) and those choosing not to (control group).

3.5. Tail climate risks and adaptation measures

According to previous results, tail transition risk influences systemic risk in the financial sector and more strongly affects financial institutions that exhibit specific financial and extrafinancial characteristics. In this section, we investigate whether financial institutions take action to adapt to tail climate risks. Our results are reported in Table A.11.

In Panel A, we assess the impact, if any, of tail transition risk on managers' disclosure of ESG and climate information. This initial analysis is in the spirit of Campbell et al. (2014), who show that firms are more likely to disclose information about a risk when they are materially exposed to it. Furthermore, we investigate whether financial institutions most exposed to transition risk use carbon offsetting to decrease net GHG emissions and engage more with policymakers on climate-related issues, which are two plausible forms of transition risk management.

In column (1), we start by analyzing the Management Discussion and Analysis (MD&A) section, which provides managers' key comments in annual reports. The MD&A section allows flexible communication (Brown et al., 2021). We assess whether higher transition risk increases the probability of integrating ESG information in the MD&A section after controlling for the natural logarithm of market capitalization, net income, market-to-book, cash, beta, debt, and industry-year and country-year fixed effects.[28] All of our control variables are lagged by one year to mitigate potential endogeneity issues. In column (2), we assess more specifically whether transition risk increases the propensity to discuss climate risk in the MD&A section.

[28] Since the fiscal year 2017, the European Union's Non-Financial Reporting Directive (NFRD) mandates banks and insurance companies with more than 500 companies to publish a nonfinancial report. This report should cover the following dimensions: environment, social and employee-related matters, respect for human rights, anti-corruption and bribery matters. However, financial institutions can either publish a separate nonfinancial report or integrate the information into the management report (MD&A), and the NFRD does not explicitly mention climate matters (see here).

We further control for the environmental transparency score in columns (3) and (4). Across our specifications, our findings indicate a positive and significant effect of tail transition risk on managers' disclosure of ESG and climate information after controlling for other potential determinants of environmental disclosure. A one standard deviation increase in exposure to transition risk is associated with a 1.8 to 4.9 percentage point increase in the probability of disclosing ESG and climate information in the MD&A section. In unreported tests, we control for the ESG transparency score instead of the environmental transparency score. Our results are qualitatively identical. Overall, these results indicate that exposure to transition risk leads managers to disclose information through the MD&A section, a flexible communication channel, which might allow them to pursue a strategy of selective disclosure.

In column (5), we further find some statistically insignificant evidence that, all else being equal, financial institutions with higher exposure to transition risk engage more in carbon offsetting. This result is consistent with a risk management perspective, whereby financial institutions attempt to decrease their exposure to transition risk by lowering their net GHG emissions through carbon offsetting. One caveat of this test is that our measure does not distinguish between the various types of carbon offsetting. Nonetheless, we can reasonably expect that these carbon offsets primarily pertain to Scope 3 emissions, which represent the vast majority of financial institutions' GHG emissions.[29] Finally, we find in column (6) that institutions with greater exposure to tail transition risk are less likely to engage with policymakers in possible responses to climate change. This result provides evidence against the view that climate regulators can be captured by the riskiest financial institutions. In a similar vein, the findings of Schneider et al. (2023) indicate that larger trading banks (i.e., those most

[29] This survey from CDP finds that financial institutions' Scope 3 emissions coming from investments are over 700 times larger than the emissions coming from their own operations.

likely to be “Too Big to Fail”) face the toughest stress tests, a finding they interpret as going against regulatory capture concerns.

Since physical risk does not appear material for financial institutions over our sample period, we do not expect that physical risk should significantly affect climate disclosure. However, as most investors expect physical risk to become material within a few years (Krueger et al., 2020), financial institutions might already take action to address it. In Panel B, we therefore analyze the impact of tail physical risk on financial institutions’ proactive climate risk management initiatives. We analyze the impact of physical risk on the creation of an internal team of environmental specialists (column 1), the launching of environmental products (column 2), and the use of climate scenario analysis (column 3). Our results indicate that a one-standard-deviation increase in physical risk leads to a 4.2 to 6.2 percentage point increase in the probability of engaging in such initiatives. Unlike nonfinancial disclosure, which is readily available to investors, or an immediate lowering of net GHG emissions through offsetting, these internal initiatives create a structure that might have effects only in the long run.

Finally, in unreported robustness tests, we verify that all the results documented in Table A.11 are robust to the use of alternative fixed effect combinations, such as industry and year fixed effects; country, industry, and year fixed effects; country-year and industry fixed effects; and country-industry-year fixed effects. Overall, our results indicate that exposure to tail climate risks influences financial institutions’ disclosure strategy and their propensity to engage in various initiatives to mitigate the future effects of climate risks on their activities.

4. Conclusion

The potential impact of climate change on financial stability is a source of growing concern for central banks, financial supervisors, and society as a whole. In this study, we introduce a novel framework for analyzing systemic climate risk, leveraging environmental and stock market data. We then apply our approach to a sample of large European financial institutions. Our findings reveal that many financial institutions are positively and significantly exposed to tail transition risk. Moreover, we observe a continuous increase in exposure to transition risk since 2015, which is particularly pronounced among banks, life insurance companies, and nonlife insurance companies. Finally, our research shows that transition climate risk can magnify tail dependence among financial institutions, which is a critical aspect of systemic risk. In contrast, our analysis does not find evidence of contagion effects in the case of physical climate risk. This observation may be attributed to the moderate intensity and asynchronous nature of natural disasters on a European scale.

In addition, our results show that exposure to tail climate risks is lower for financial institutions committed to environmental risk management, as well as for those with greater transparency and long-term orientation. Some recent ESG regulations also seem to decrease risk levels. Moreover, we highlight that financial institutions with cleaner investment and lending portfolios tend to be less exposed to transition risk. In summary, our findings suggest that regulators and managers of financial institutions have the ability to reduce systemic climate risk. Since climate shocks appear to affect both individual risk and tail dependence in the financial sector, we contend that the characteristics we find associated with exposure to climate risks hold relevance for the development of both microprudential and macroprudential climate risk regulations.

Owing to the forward-looking nature of market prices, our market-based framework is more responsive than other accounting-based models. This approach allows for dynamic monitoring of the prevalence of systemic climate risk. We assert that market perception is critical for financial institutions because the threat that climate risks pose to financial stability depends largely on investors' repricing of financial assets. Consequently, our results hold potential significance for informing the development of climate scenarios and assumptions about the future impact of climate risks on asset prices. The framework we design in this paper is flexible and can be applied to diverse contexts, including other countries, sectors, asset types, or periods. It can also be used to assess the influence of other emerging threats to financial stability, such as cybersecurity or biodiversity risk, provided that relevant time series representing variations in the risk source are available. Portfolio managers could also use our framework as a practical risk management tool to assess the exposure of their portfolios to extreme climate risks.

However, two caveats apply. First, our results must be interpreted with some caution. They primarily reflect the extent to which investors perceive the effect of tail climate risks on financial stability. Notably, investors may not be fully able to incorporate complex climate science information into prices, and this ability may vary over time. Furthermore, the long-term nature of climate risks may make the results sensitive to variations in discount rates. Second, we acknowledge the methodological challenges of our study, such as separating climate risk from other risk factors; as well as disentangling various channels of contagion, namely, common risk exposures, spillover effects, and pure contagion, which may represent fruitful areas for future research. These caveats notwithstanding, we believe that our results can improve the current understanding of the financial consequences of climate risks and climate-related decision-making.

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Appendix A: Figures and Tables

Figure A.1

Variance explained by the principal components

This figure represents the variance explained by each principal component (gray bars) extracted from Σ_{std}, the correlation matrix between time variations in the VaR of financial institutions (Equations 1 and 2), and the cumulative variance explained by the first ten principal components (black line).

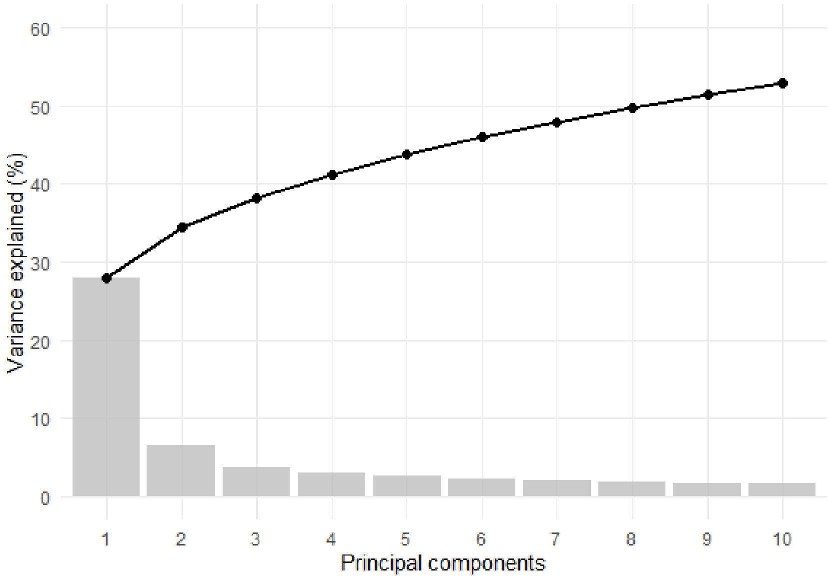


Figure A.2

Time variations in systemic risk

The indicator represents the first principal component Ω_1, which accounts for the common variations in the VaR of financial institutions. The chart on the left represents changes in the systemic risk indicator (Equation 3), whereas the chart on the right represents levels, reflecting the cumulative effect of shocks on the systemic risk indicator (January 2005 = 100).

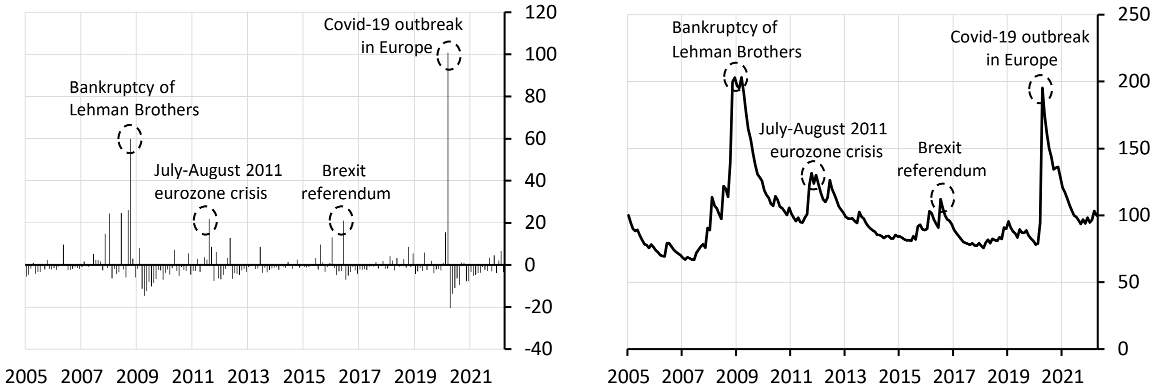


Figure A.3

Distribution of exposure to tail climate risks by type of financial institution

The figure represents the distribution, based on a density function, of the vectors of financial institutions' exposure to climate risks, $\hat{\beta}_{BMG}$ and $\hat{\beta}_{VMS}$, estimated in Equation (8) over the entire period (2005–2022). The left panel provides details by type of financial institution for $\hat{\beta}_{BMG}$, the indicator of exposure to transition risk. The right panel provides details by type of financial institution for $\hat{\beta}_{VMS}$, the indicator of exposure to physical risk. The acronyms REIT and REIS stand for "real estate investment trusts" and "real estate investment services", respectively.

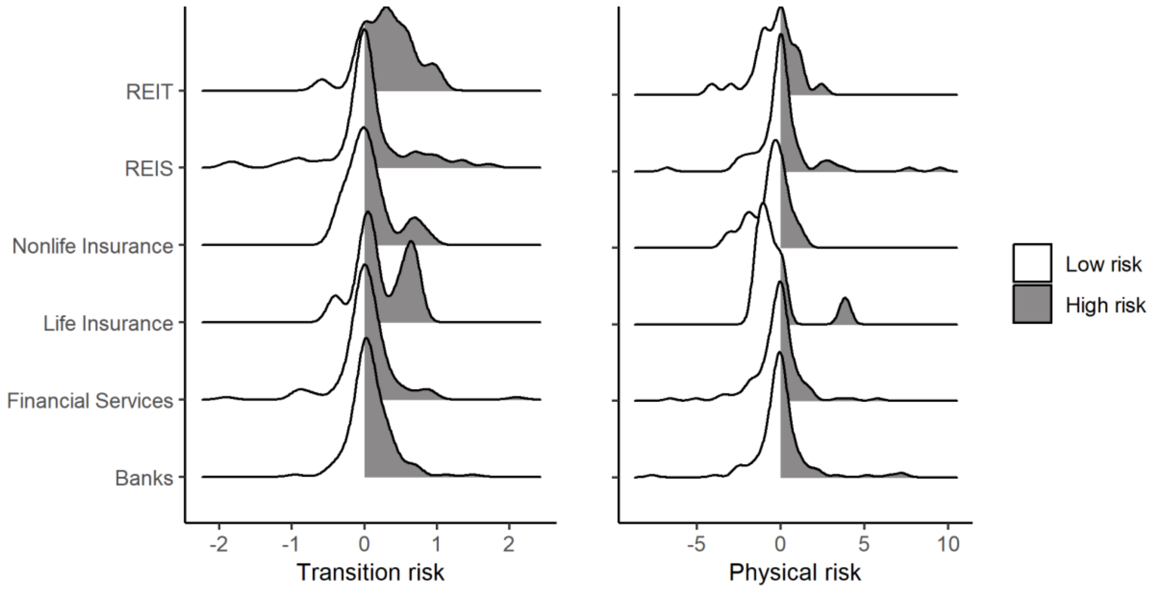


Figure A.4

Exposure to tail climate risks by country

This map represents the geographical distribution of financial institutions' exposure to climate risks, $\hat{\beta}_{BMG}$ and $\hat{\beta}_{VMS}$, estimated in Equation (8) over the entire period (2005–2022). The left-hand panel provides details by country for $\hat{\beta}_{BMG}$, the indicator of exposure to transition risk. The right-hand panel provides details by country for $\hat{\beta}_{VMS}$, the indicator of exposure to physical risk. For each country, we calculate the weighted average of the coefficients of exposure to climate risks of national financial institutions. The weights are based on the average market value of each financial institution from 2005–2022.

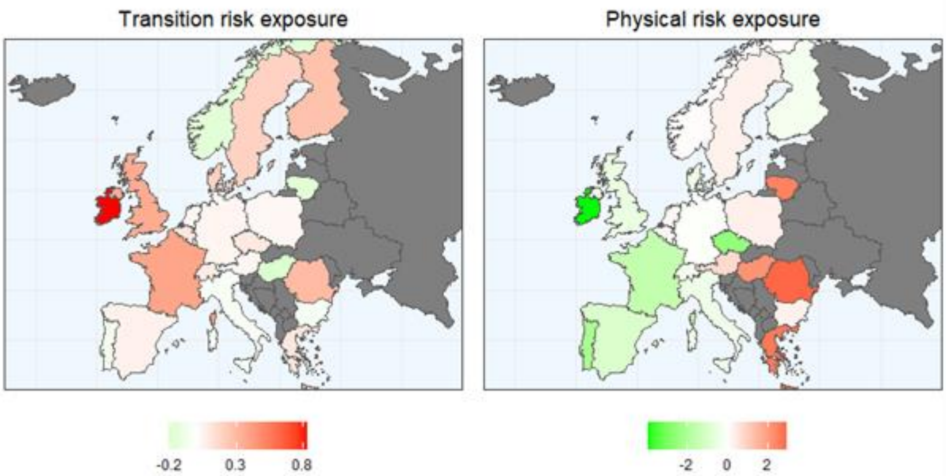
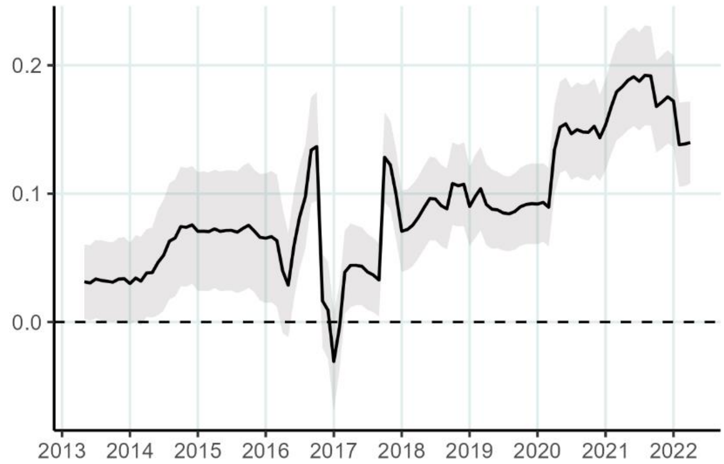


Figure A.5

Dynamic exposure to tail climate risks for all financial institutions

This figure represents the average dynamics of financial institutions' exposure to climate risks, estimated via Equation (8). To obtain dynamic individual coefficients, we estimate the model dynamically based on rolling windows of 100 observations. Next, we compute the cross-sectional mean (black line) and the 95% confidence interval (gray area) for each period. We use the mean-group estimator (Pesaran and Smith, 1995) on the basis of a robust regression of individual estimates on a single cross-sectional unit. Panel A provides details for $\hat{\beta}_{BMG}$, the indicator of exposure to transition risk. Panel B provides details for $\hat{\beta}_{VMS}$, the indicator of exposure to physical risk.

Panel A: Transition risk exposure



Panel B: Physical risk exposure

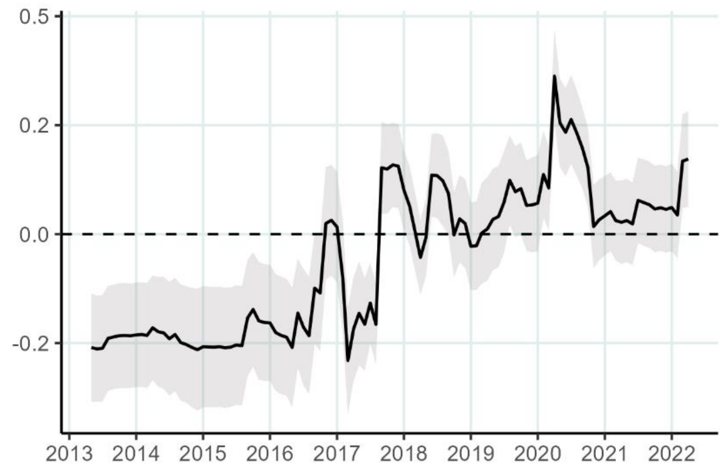


Figure A.6

Dynamic exposure to tail transition risk by type of financial institution

This figure represents the average dynamics of financial institutions' exposure to transition risk, $\hat{\beta}_{BMG}$, estimated via Equation (8). To obtain dynamic individual coefficients, we estimate the model dynamically based on rolling windows of 100 observations. Next, we compute the cross-sectional mean (black line) and the 95% confidence interval (gray area) for each period. We use the mean-group estimator (Pesaran and Smith, 1995) on the basis of a robust regression of individual estimates on a single cross-sectional unit. We provide details for each financial industry. The acronyms REIT and REIS stand for "real estate investment trusts" and "real estate investment services", respectively.

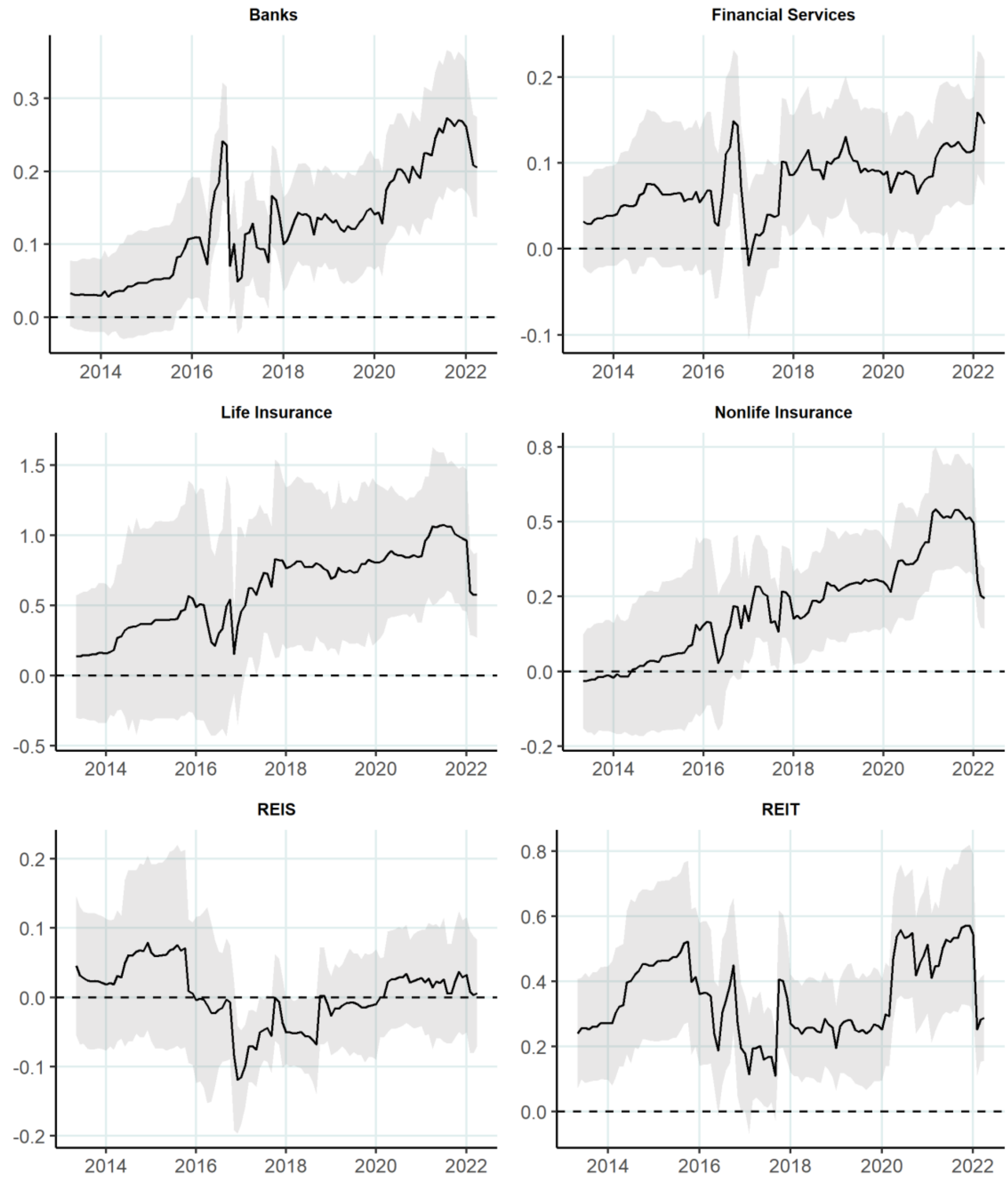


Figure A.7

Dynamic exposure to tail physical risk by type of financial institution

This figure represents the average dynamics of financial institutions' exposures to physical risk, $\hat{\beta}_{VMS}$, estimated in Equation (8). To obtain dynamic individual coefficients, we estimate the model dynamically based on rolling windows of 100 observations. Next, we compute the cross-sectional mean (black line) and the 95% confidence interval (gray area) for each period. We use the mean-group estimator (Pesaran and Smith, 1995) on the basis of a robust regression of individual estimates on a single cross-sectional unit. We provide details for each financial industry. The acronyms REIT and REIS stand for "real estate investment trusts" and "real estate investment services", respectively.

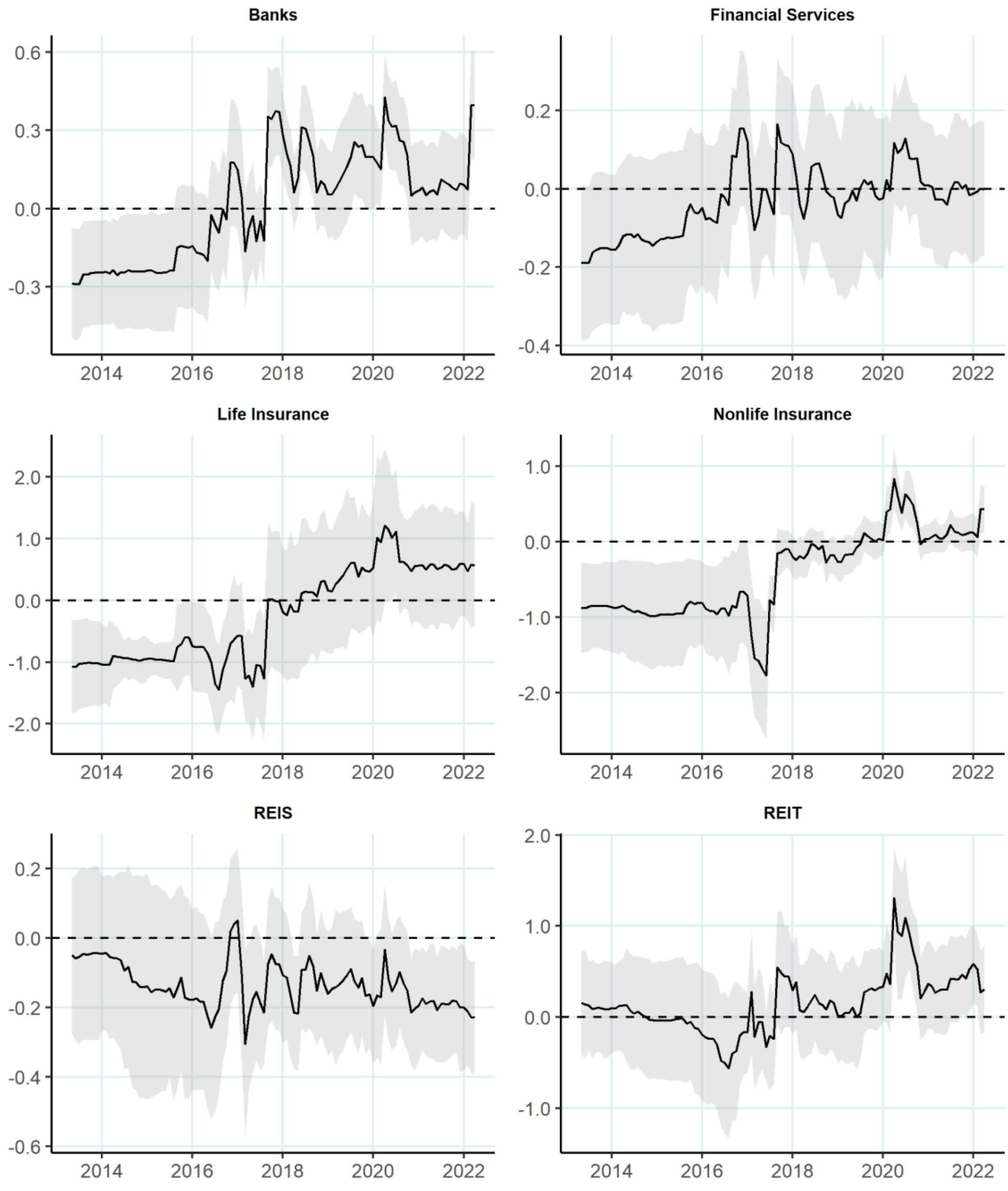


Figure A.8

Dynamic exposure to tail transition risk by country

This figure represents the average dynamics of financial institutions' exposure to transition risk, $\hat{\beta}_{BMG}$, estimated via Equation (8). To obtain dynamic individual coefficients, we estimate the model dynamically based on rolling windows of 100 observations. Next, we compute the cross-sectional mean (black line) and the 95% confidence interval (gray area) for each period. We use the mean-group estimator (Pesaran and Smith, 1995) on the basis of a robust regression of individual estimates on a single cross-sectional unit. We provide details for the countries most represented in our sample of financial institutions.

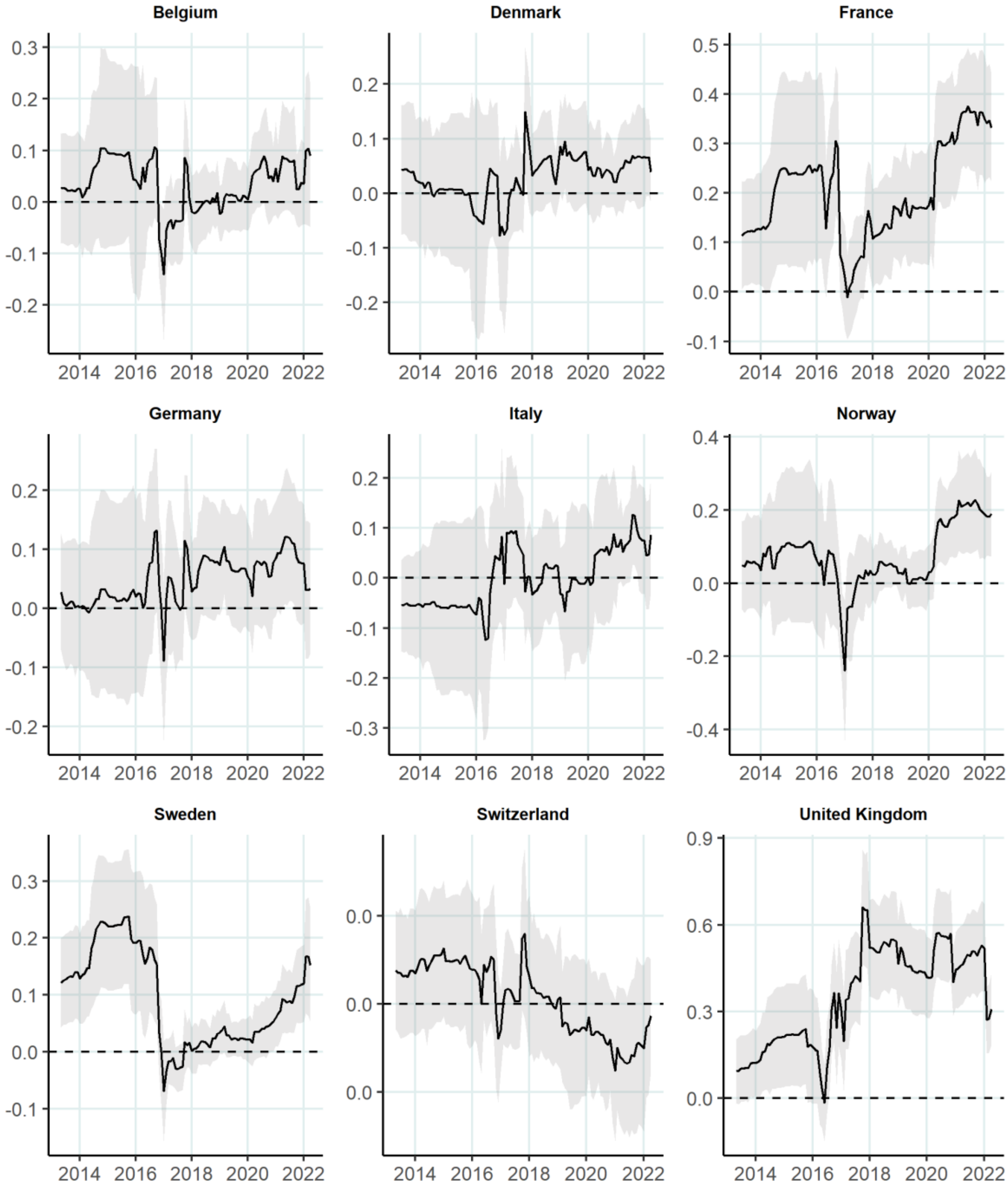


Figure A.9

Dynamic exposure to tail physical risk by country

This figure represents the average dynamics of financial institutions' exposures to physical risk, $\hat{\beta}_{VMS}$, estimated in Equation (8). To obtain dynamic individual coefficients, we estimate the model dynamically based on rolling windows of 100 observations. Next, we compute the cross-sectional mean (black line) and the 95% confidence interval (gray area) for each period. We use the mean-group estimator (Pesaran and Smith, 1995) on the basis of a robust regression of individual estimates on a single cross-sectional unit. We provide details for the countries most represented in our sample of financial institutions.

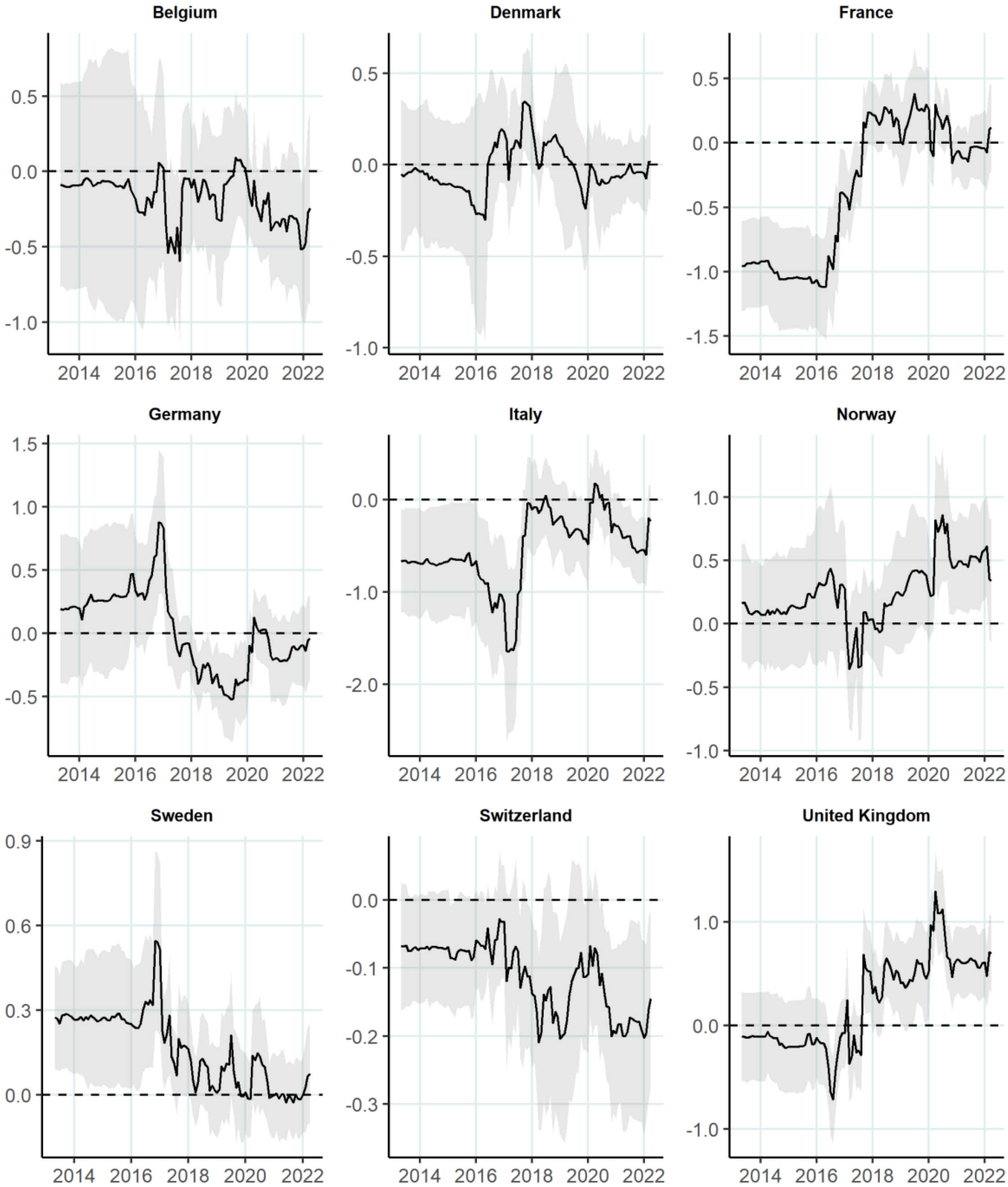


Table A.1

Descriptive statistics of financial institutions

This table presents the summary statistics of the characteristics of the financial institutions in our sample. Appendix B presents the variable definitions. The sample comprises all European financial institutions from 2005–2022, with an average market capitalization above €100 million over the entire period. $\hat{\beta}_{BMG_{i,avg}}$ and $\hat{\beta}_{VMS_{i,avg}}$ are the indicators of exposure to climate risks estimated statically in Equation (8) over the period 2005–2022, whereas $\hat{\beta}_{BMG_{i,t}}$ and $\hat{\beta}_{VMS_{i,t}}$ are estimated dynamically on a rolling window of 100 observations.

VARIABLES	N	Mean	SD	Median	P25	P75
Institution-level characteristics						
$\hat{\beta}_{BMG_{i,avg}}$	6,350	0.081	0.385	0.025	-0.072	0.222
$\hat{\beta}_{VMS_{i,avg}}$	6,350	-0.120	1.564	-0.034	-0.664	0.251
$\hat{\beta}_{BMG_{i,t}}$	3,242	0.110	0.588	0.030	-0.084	0.320
$\hat{\beta}_{VMS_{i,t}}$	3,242	0.076	1.962	-0.004	-0.625	0.533
Beta	6,350	0.824	0.559	0.760	0.392	1.175
LogMarketValue	6,350	6.454	2.128	6.395	4.836	7.918
Cash	6,350	0.046	0.092	0.006	0.000	0.047
NetIncome	6,350	0.023	0.070	0.010	0.003	0.041
MtoB	6,350	1.276	1.192	0.972	0.629	1.479
Debt	6,350	45.920	30.216	46.585	19.180	74.900
LowScope3	1,842	0.106	0.308	0.000	0.000	0.000
VerifiedScope3	1,017	0.688	0.463	1.000	0.000	1.000
ReductionTargetReached	813	0.851	0.356	1.000	1.000	1.000
Board LT incentives	6,253	0.065	0.433	0.000	0.000	0.000
Institutional ownership	2,642	0.142	0.195	0.072	0.012	0.182
IntegratedStrategy	6,415	0.083	0.275	0.000	0.000	0.000
DiscussClimateRisk	2,621	0.253	0.435	0.000	0.000	1.000
LogCarbonOffsets	524	9.558	2.614	9.349	7.881	11.299
PolicyEngagement	1,700	0.747	0.435	1.000	0.000	1.000
EnvironmentalTeam	6,350	0.166	0.372	0.000	0.000	0.000
EnvironmentalProducts	2,596	0.457	0.498	0.000	0.000	1.000
ClimateScenarioAnalysis	1,218	0.201	0.401	0.000	0.000	0.000
Country-level characteristics						
HighRenewables	6,265	0.245	0.430	0.000	0.000	0.000
LowEmissions	6,117	0.184	0.387	0.000	0.000	0.000
LowEmissionsPerCapita	6,117	0.214	0.410	0.000	0.000	0.000
LogEmissions	6,117	12.203	1.108	12.796	10.981	13.268
Floods	6,350	0.725	0.067	0.735	0.670	0.777
Deaths	6,350	0.088	0.283	0.000	0.000	0.000
WaterDependency	6,350	0.151	0.200	0.052	0.014	0.245
ESGmandate	6,350	0.487	0.500	0.000	0.000	1.000

Table A.2

Correlation matrix for tail risk factors

This table presents the correlation matrix among the ΔVaR risk factors. Appendix B presents the variable definitions.

	BMG	VMS	MKT	SMB	HML	RMW	CMA	WML	RR	ML	DP	YC	NS
VMS	-5%												
MKT	0%	25%											
SMB	10%	15%	25%										
HML	-22%	13%	37%	33%									
RMW	-1%	10%	31%	15%	47%								
CMA	19%	17%	32%	23%	-2%	15%							
WML	21%	26%	26%	15%	21%	22%	17%						
RR	4%	0%	-2%	-1%	-14%	-11%	11%	-11%					
ML	-5%	12%	29%	27%	11%	33%	13%	12%	-13%				
DP	-3%	26%	80%	41%	41%	38%	29%	32%	-1%	39%			
YC	-4%	1%	3%	-4%	4%	2%	1%	5%	5%	12%	8%		
NS	-6%	9%	16%	-2%	17%	-4%	1%	8%	6%	3%	7%	27%	
ES	-7%	13%	47%	46%	63%	12%	12%	19%	4%	7%	47%	1%	17%

Table A.3

Variance decomposition

This table presents a variance decomposition of the individual tail climate risk indicators. The following equation is estimated: $Climate\ risk_{i,t} = \alpha + \beta X_{i,t} + \varepsilon_{i,t}$. Columns (1) and (2) use $\hat{\beta}_{BMG}$, our measure of tail transition risk, as the dependent variable. In columns (3) and (4), $\hat{\beta}_{VMS}$, our measure of tail physical risk, is used as the dependent variable. $\hat{\beta}_{BMG}$ and $\hat{\beta}_{VMS}$ are estimated dynamically on a rolling window of 100 observations from Equation (8). $X_{i,t}$ is a vector of fixed effects. $\varepsilon_{i,t}$ is the error term. For each line in the table, the information in bold represents the fixed effect that is added compared with the previous line, and its incremental R-squared is reported in italics. Columns (1) and (3) use the total sample. Columns (2) and (4) restrict the sample to countries with more than 100 institution-year observations.

FIXED EFFECTS	(1) $\hat{\beta}_{BMG_{i,t}}$	(2) $\hat{\beta}_{BMG_{i,t}}$	(3) $\hat{\beta}_{VMS_{i,t}}$	(4) $\hat{\beta}_{VMS_{i,t}}$
	Total sample	Only countries with more than 100 observations	Total sample	Only countries with more than 100 observations
Year	*1.43%*	*1.40%*	*1.01%*	*0.94%*
Year, **Industry**	*2.33%*	*2.27%*	*1.21%*	*1.39%*
Year, Industry, **Country**	*6.60%*	*5.52%*	*10.80%*	*9.03%*
Country, **Industry-Year**	*0.63%*	*0.79%*	*1.32%*	*1.57%*
Industry-Year, **Country-Year**	*6.35%*	*4.13%*	*10.11%*	*8.03%*
Industry-Year, Country-Year, **Institution**	*38.66%*	*39.39%*	*36.68%*	*39.20%*
Total explained by fixed effects	56.00%	53.50%	61.13%	60.16%
Total explained by firm variations	44.00%	46.50%	38.87%	39.84%

Table A.4

Determinants of systemic risk—time series dimension

This table presents the determinants of systemic risk based on the time series analysis described in Equation (7). We use Ω_1, the systemic risk measure derived from the first principal component defined in Equation (3), as the dependent variable. The independent variables are the ΔVaR of the risk factors, as described in Section 2.5, except for RR and ES, which are in first differences. Newey–West standard errors are reported in parentheses. ***, **, and * indicate significance at the 1%, 5% and 10% levels, respectively. Standardized regression coefficients are reported. A positive coefficient always indicates that a degradation in the indicator is associated with an increase in systemic risk.

VARIABLES	(1) Ω_1	(2) Ω_1	(3) Ω_1	(4) Ω_1	(5) Ω_1
BMG	0.062* (0.036)	0.080** (0.034)	0.077** (0.035)	0.049* (0.030)	0.044* (0.026)
VMS	0.008 (0.027)	-0.001 (0.034)	-0.002 (0.033)	-0.023 (0.035)	-0.017 (0.028)
MKT	0.313*** (0.091)	0.585*** (0.067)	0.580*** (0.078)	0.568*** (0.076)	0.348*** (0.080)
ML	0.033 (0.050)				-0.0004 (0.035)
DP	0.275*** (0.085)				0.169*** (0.064)
YC	0.011 (0.024)				0.017 (0.025)
NS	0.031 (0.027)				0.029 (0.022)
RR	-0.059 (0.036)				-0.021 (0.021)
ES	0.496*** (0.062)				0.376*** (0.055)
SMB		0.227*** (0.065)	0.223*** (0.069)	0.224*** (0.062)	0.109*** (0.037)
HML		0.377*** (0.099)	0.385*** (0.120)	0.370*** (0.114)	0.130* (0.071)
RMW			-0.010 (0.080)	-0.020 (0.076)	0.076 (0.055)
CMA			0.019 (0.036)	0.017 (0.032)	0.007 (0.026)
WML				0.101*** (0.038)	0.077** (0.030)
Constant	0 (0.026)	0 (0.030)	0 (0.028)	0 (0.029)	0 (0.022)
Observations	207	207	207	207	207
R-squared	0.864	0.820	0.821	0.829	0.899
Adjusted R-squared	0.858	0.816	0.814	0.822	0.892

Table A.5

Determinants of systemic risk—cross-sectional dimension

This table presents the results of the cross-sectional analysis, as described in Equation (9). The dependent variable X_1 represents the loading of each financial institution on Ω_1. The explanatory variables are the coefficients $\hat{\beta}$ extracted from Equation (8). White heteroskedasticity-robust standard errors are reported in parentheses in columns (1) to (4). We include industry and country fixed effects and report clustered standard errors at the country level in columns (5) to (8).

VARIABLES	(1) X_1	(2) X_1	(3) X_1	(4) X_1	(5) X_1	(6) X_1	(7) X_1	(8) X_1
$\hat{\beta}_{BMG}$	0.006**	0.012***	0.012***	0.007**	0.006*	0.010**	0.012***	0.008***
	(0.003)	(0.004)	(0.004)	(0.003)	(0.002)	(0.003)	(0.004)	(0.003)
$\hat{\beta}_{VMS}$	0.001	-0.001	-0.0001	0.001	0.001	-0.001	-0.001	0.002
	(0.001)	(0.001)	(0.001)	(0.001)	(0.001)	(0.001)	(0.001)	(0.001)
$\hat{\beta}_{MKT}$	0.030***	0.013***	0.011***	0.026***	0.024***	0.011	0.009	0.020***
	(0.004)	(0.004)	(0.004)	(0.004)	(0.003)	(0.006)	(0.006)	(0.003)
$\hat{\beta}_{ML}$	0.0003**			0.0005***	0.0002			0.0003***
	(0.000)			(0.000)	(0.000)			(0.000)
$\hat{\beta}_{DP}$	0.007***			0.007***	0.007***			0.007***
	(0.001)			(0.001)	(0.001)			(0.001)
$\hat{\beta}_{YC}$	-0.004**			-0.002	-0.003			-0.002
	(0.002)			(0.002)	(0.002)			(0.002)
$\hat{\beta}_{NS}$	-0.002*			-0.003***	-0.002**			-0.004***
	(0.001)			(0.001)	(0.001)			(0.001)
$\hat{\beta}_{RR}$	-0.002			-0.006**	-0.004			-0.009***
	(0.002)			(0.003)	(0.003)			(0.003)
$\hat{\beta}_{ES}$	0.063***			0.053***	0.056***			0.051***
	(0.006)			(0.007)	(0.003)			(0.009)
$\hat{\beta}_{SMB}$		0.004***	0.003***	0.003***		0.003***	0.003***	0.004***
		(0.001)	(0.001)	(0.001)		(0.000)	(0.001)	(0.001)
$\hat{\beta}_{HML}$		0.004***	0.005**	0.007***		0.002	0.004	0.004
		(0.002)	(0.002)	(0.002)		(0.002)	(0.003)	(0.003)
$\hat{\beta}_{RMW}$			0.001	0.001			0.001	0.001
			(0.001)	(0.001)			(0.001)	(0.001)
$\hat{\beta}_{CMA}$			0.004	0.005***			0.004	0.005*
			(0.003)	(0.002)			(0.004)	(0.003)
$\hat{\beta}_{WML}$			0.030***	0.01			0.017*	0.005
			(0.009)	(0.006)			(0.009)	(0.009)
Constant	0.015***	0.026***	0.023***	0.013***				
	(0.003)	(0.003)	(0.003)	(0.003)				
Observations	371	371	371	371	371	371	371	371
R-squared	0.341	0.14	0.171	0.377	0.451	0.306	0.318	0.478
Adjusted R-squared	0.325	0.128	0.152	0.352	0.389	0.236	0.242	0.409
Country Fixed Effects	No	No	No	No	Yes	Yes	Yes	Yes
Industry Fixed Effects	No	No	No	No	Yes	Yes	Yes	Yes

Table A.6

Tail transition risk and characteristics of financial institutions

This table presents the characteristics associated with financial institutions' exposure to transition risk, $\hat{\beta}_{BMG}$, estimated from Equation (8). In columns (1) and (2), $\hat{\beta}_{BMG}$ is estimated statically over the entire period (2005–2022), and heteroskedasticity-robust standard errors are reported in parentheses. In columns (3) to (8), $\hat{\beta}_{BMG}$ is estimated dynamically on a rolling window of 100 observations, and standard errors clustered at the institution level are reported in parentheses. Regression (2) uses country and industry fixed effects. Regressions (3) and (4) use country, industry, and year fixed effects. Regressions (5) to (8) use institution and year fixed effects. Appendix B presents the variable definitions. ***, **, and * indicate significance at the 1%, 5% and 10% levels, respectively.

VARIABLES	(1) $\hat{\beta}_{BMG_{i,avg}}$	(2) $\hat{\beta}_{BMG_{i,avg}}$	(3) $\hat{\beta}_{BMG_{i,t}}$	(4) $\hat{\beta}_{BMG_{i,t}}$	(5) $\hat{\beta}_{BMG_{i,t}}$	(6) $\hat{\beta}_{BMG_{i,t}}$	(7) $\hat{\beta}_{BMG_{i,t}}$	(8) $\hat{\beta}_{BMG_{i,t}}$
Beta (t-1)	0.0442*** (0.0113)	0.0209* (0.0112)	-0.0328 (0.0579)	-0.0864 (0.0963)	-0.368** (0.171)	-0.336** (0.146)	-0.0702 (0.0825)	-0.00119 (0.0715)
LogMarketValue (t-1)	0.0218*** (0.00267)	0.0228*** (0.00277)	0.0524*** (0.0131)	0.0468* (0.0280)	0.0558 (0.141)	0.0989 (0.163)	0.0709 (0.0696)	0.0422 (0.0604)
Cash (t-1)	-0.196*** (0.0588)	-0.168*** (0.0627)	-0.122 (0.197)	-1.871** (0.831)	-0.682 (0.953)	-0.973 (0.753)	-0.177 (0.293)	0.0347 (0.308)
NetIncome (t-1)	0.318*** (0.0922)	0.237*** (0.0907)	0.229 (0.227)	-0.985 (0.769)	-1.765** (0.812)	-0.467 (0.754)	-0.0635 (0.215)	0.0905 (0.215)
MtoB (t-1)	0.00765* (0.00452)	0.00284 (0.00443)	-0.0191 (0.0145)	-0.0402 (0.0322)	0.280** (0.116)	0.189 (0.131)	-0.0488 (0.0364)	-0.0751 (0.0485)
Debt (t-1)	0.000646*** (0.000176)	0.00120*** (0.000231)	0.00219** (0.000990)	0.00284 (0.00249)	0.00112 (0.00431)	0.00633 (0.00475)	0.00240 (0.00226)	-0.000103 (0.00186)
LowScope3 (t-1)				-0.205** (0.0905)				
VerifiedScope3 (t-1)					-0.299** (0.129)			
ReductionTargetReached (t-1)						-0.101* (0.0606)		
Board LT incentives (t-1)							-0.0738** (0.0367)	
Institutional ownership (t-1)								-0.282*** (0.101)
Constant	-0.133*** (0.0190)	-0.321*** (0.0770)	-0.358** (0.158)	-0.472* (0.260)	0.155 (1.273)	-0.582 (1.351)	-0.230 (0.485)	0.102 (0.405)
Observations	5,992	5,992	3,245	945	715	699	3,245	2,222
R-squared	0.038	0.166	0.138	0.211	0.604	0.665	0.498	0.655
Adjusted R-squared	0.037	0.161	0.127	0.182	0.543	0.580	0.432	0.588
Country Fixed Effects	No	Yes	Yes	Yes				
Industry Fixed Effects	No	Yes	Yes	Yes				
Institution Fixed Effects	No	No	No	No	Yes	Yes	Yes	Yes
Year Fixed Effects	No	No	Yes	Yes	Yes	Yes	Yes	Yes

Table A.7

Tail physical risk and characteristics of financial institutions

This table presents the characteristics associated with financial institutions' exposure to physical risk, $\hat{\beta}_{VMS}$, estimated from Equation (8). In columns (1) and (2), $\hat{\beta}_{VMS}$ is estimated statically, and heteroskedasticity-robust standard errors are reported in parentheses. In columns (3) to (5), $\hat{\beta}_{VMS}$ is estimated dynamically on a rolling window of 100 observations, and standard errors clustered at the institution level are reported in parentheses. Regression (2) uses country and industry fixed effects. Regression (3) uses country, industry, and year fixed effects. Regressions (4) and (5) use institution and year fixed effects. Appendix B presents the variable definitions. ***, **, and * indicate significance at the 1%, 5% and 10% levels, respectively.

VARIABLES	(1) $\hat{\beta}_{VMS_{i,avg}}$	(2) $\hat{\beta}_{VMS_{i,avg}}$	(3) $\hat{\beta}_{VMS_{i,t}}$	(4) $\hat{\beta}_{VMS_{i,t}}$	(5) $\hat{\beta}_{VMS_{i,t}}$
Beta (t-1)	0.301***	0.325***	0.410*	0.0650	-0.430
	(0.0537)	(0.0494)	(0.222)	(0.315)	(0.291)
LogMarketValue (t-1)	-0.102***	-0.0565***	-0.0471	-0.437**	-0.411*
	(0.0109)	(0.0113)	(0.0444)	(0.187)	(0.219)
Cash (t-1)	-0.0436	0.570**	-0.0587	-0.0496	0.804
	(0.199)	(0.223)	(0.559)	(0.534)	(0.559)
NetIncome (t-1)	0.568*	0.505	0.177	0.252	-0.146
	(0.325)	(0.328)	(0.745)	(0.654)	(0.797)
MtoB (t-1)	-0.0446**	-0.0309*	-0.0203	0.116	0.227**
	(0.0192)	(0.0178)	(0.0775)	(0.0948)	(0.0993)
Debt (t-1)	0.00298***	0.000971	-0.000277	-0.00460	0.00798
	(0.000735)	(0.000855)	(0.00332)	(0.00705)	(0.00778)
Board LT incentives (t-1)				-0.0244	
				(0.159)	
Institutional ownership (t-1)					-0.0931
					(0.324)
Constant	0.197***	1.609***	0.633	3.183**	2.532
	(0.0684)	(0.236)	(0.636)	(1.406)	(1.553)
Observations	5,992	5,992	3,245	3,245	2,222
R-squared	0.022	0.218	0.138	0.504	0.642
Adjusted R-squared	0.021	0.213	0.127	0.439	0.572
Country Fixed Effects	No	Yes	Yes		
Industry Fixed Effects	No	Yes	Yes		
Institution Fixed Effects	No	No	No	Yes	Yes
Year Fixed Effects	No	No	Yes	Yes	Yes

Table A.8

Tail transition risk and country characteristics

This table presents the associations between country-level climate characteristics and financial institutions' exposure to transition climate risk, $\hat{\beta}_{BMG}$. $\hat{\beta}_{BMG}$ is estimated dynamically on a rolling window of 100 observations from Equation (8). Country-level climate characteristics are taken from Our World in Data (University of Oxford) and the OECD data platform (Organization for Economic Cooperation and Development). Column (1) uses $HighRenewables$, a dummy variable equal to one if the institution's country is in the top quartile of renewable energy usage. Column (2) uses $LowEmissions$, a dummy variable equal to one if the institution's country is in the bottom quartile of greenhouse gas (GHG) emissions. Column (3) uses $LowEmissionsPerCapita$, a dummy variable equal to one if the institution's country is in the bottom quartile of GHG emissions per capita. Column (4) uses $LogEmissions$, the natural logarithm of the institution's country's GHG emissions. All regressions use industry and year fixed effects. Standard errors clustered at the institution level are reported in parentheses. Appendix B presents the variable definitions. ***, **, and * indicate significance at the 1%, 5% and 10% levels, respectively.

VARIABLES	(1) $\hat{\beta}_{BMG_{i,t}}$	(2) $\hat{\beta}_{BMG_{i,t}}$	(3) $\hat{\beta}_{BMG_{i,t}}$	(4) $\hat{\beta}_{BMG_{i,t}}$
Beta (t-1)	-0.000572 (0.0601)	-0.0223 (0.0644)	-0.00614 (0.0627)	-0.00392 (0.0651)
LogMarketValue (t-1)	0.0493*** (0.0134)	0.0463*** (0.0140)	0.0495*** (0.0142)	0.0464*** (0.0143)
Cash (t-1)	0.0394 (0.184)	0.0365 (0.187)	-0.0153 (0.182)	-0.0418 (0.183)
NetIncome (t-1)	0.335 (0.216)	0.320 (0.210)	0.373* (0.214)	0.370* (0.214)
MtoB (t-1)	0.00864 (0.0137)	0.00559 (0.0137)	0.00613 (0.0136)	0.00431 (0.0136)
Debt (t-1)	0.00181* (0.00102)	0.00183* (0.00104)	0.00161 (0.00103)	0.00156 (0.00103)
HighRenewables (t-1)	-0.115*** (0.0418)			
LowEmissions (t-1)		-0.138*** (0.0429)		
LowEmissionsPerCapita (t-1)			-0.127*** (0.0422)	
LogEmissions (t-1)				0.0529*** (0.0183)
Constant	-0.362*** (0.0934)	-0.327*** (0.0904)	-0.361*** (0.0928)	-0.997*** (0.258)
Observations	3,200	3,122	3,122	3,122
R-squared	0.078	0.076	0.076	0.078
Adjusted R-squared	0.072	0.070	0.070	0.072
Industry Fixed Effects	Yes	Yes	Yes	Yes
Year Fixed Effects	Yes	Yes	Yes	Yes

Table A.9

Tail physical risk and country characteristics

This table presents the associations between country-level climate characteristics and financial institutions' exposure to physical climate risk, $\hat{\beta}_{VMS}$. $\hat{\beta}_{VMS}$ is estimated dynamically on a rolling window of 100 observations from Equation (8). Country-level climate characteristics are taken from the Notre Dame Global Adaptation Initiative (ND-GAIN). Column (1) uses $Floods$, the projected change in flood hazard. Column (2) uses $Deaths$, the projected loss of life years. Column (3) uses $WaterDependency$, the proportion of water resources originating from outside the country. All regressions use industry and year fixed effects. Standard errors clustered at the institution level are reported in parentheses. Appendix B presents the variable definitions. ***, **, and * indicate significance at the 1%, 5% and 10% levels, respectively.

VARIABLES	(1) $\hat{\beta}_{VMS_{i,t}}$	(2) $\hat{\beta}_{VMS_{i,t}}$	(3) $\hat{\beta}_{VMS_{i,t}}$
Beta (t-1)	0.459* (0.257)	0.408 (0.263)	0.478* (0.261)
LogMarketValue (t-1)	-0.101** (0.0475)	-0.0786* (0.0473)	-0.105** (0.0490)
Cash (t-1)	-0.0199 (0.515)	0.126 (0.475)	-0.154 (0.510)
NetIncome (t-1)	-0.145 (0.759)	0.310 (0.710)	0.276 (0.742)
MtoB (t-1)	-0.0151 (0.0788)	-8.84e-05 (0.0731)	0.0174 (0.0798)
Debt (t-1)	-0.00281 (0.00294)	-0.00164 (0.00301)	-0.00314 (0.00293)
Floods (t-1)	3.133*** (1.032)		
Deaths (t-1)		0.786** (0.329)	
WaterDependency (t-1)			0.686* (0.358)
Constant	-1.197 (0.820)	0.740** (0.315)	0.960*** (0.293)
Observations	3,245	3,245	3,245
R-squared	0.049	0.050	0.043
Adjusted R-squared	0.043	0.044	0.037
Industry Fixed Effects	Yes	Yes	Yes
Year Fixed Effects	Yes	Yes	Yes

Table A.10

Staggered differences-in-differences in tail transition risk around ESG disclosure mandates

This table presents staggered difference-in-differences estimates for tail transition risk before and after ESG disclosure mandates at the country level. We use $\hat{\beta}_{BMG}$, our measure of tail transition risk, as the dependent variable. $\hat{\beta}_{BMG}$ is estimated dynamically on a rolling window of 100 observations from Equation (8). Columns (1) to (3) use country, industry, and year fixed effects. Columns (4) to (6) use institution and year fixed effects. Regressions (1) and (4) use the full sample. Regressions (2) and (5) use financial institutions with above-median exposure to transition risk. Regressions (3) and (6) use financial institutions with exposure to transition risk below or equal to the median. Standard errors are clustered at the financial institution level and are reported in parentheses. Appendix B presents the variable definitions. ***, **, and * indicate significance at the 1%, 5% and 10% levels, respectively.

VARIABLES	(1) $\hat{\beta}_{BMG_{i,t}}$	(2) $\hat{\beta}_{BMG_{i,t}}$	(3) $\hat{\beta}_{BMG_{i,t}}$	(4) $\hat{\beta}_{BMG_{i,t}}$	(5) $\hat{\beta}_{BMG_{i,t}}$	(6) $\hat{\beta}_{BMG_{i,t}}$
	Total sample	Above median Transition risk	Below median Transition risk	Total sample	Above median Transition risk	Below median Transition risk
Beta (t-1)	-0.0323 (0.0579)	0.0891 (0.0657)	-0.279*** (0.0683)	-0.0699 (0.0824)	0.0537 (0.107)	-0.266** (0.104)
LogMarketValue (t-1)	0.0523*** (0.0131)	0.00367 (0.0174)	0.0733*** (0.0143)	0.0698 (0.0695)	-0.0922 (0.0770)	0.168** (0.0820)
Cash (t-1)	-0.120 (0.197)	-0.404 (0.310)	-0.0361 (0.231)	-0.174 (0.294)	0.395 (0.543)	-0.130 (0.296)
NetIncome (t-1)	0.235 (0.227)	0.327 (0.343)	0.0557 (0.220)	-0.0549 (0.215)	0.0849 (0.378)	-0.0309 (0.213)
MtoB (t-1)	-0.0195 (0.0145)	-0.0134 (0.0223)	-0.0258 (0.0181)	-0.0502 (0.0367)	0.00345 (0.0434)	-0.0612 (0.0480)
Debt (t-1)	0.00216** (0.000987)	0.00186 (0.00136)	0.000866 (0.000943)	0.00227 (0.00227)	-0.00212 (0.00277)	0.00713** (0.00312)
ESGmandate	-0.0670 (0.0627)	-0.228*** (0.0861)	0.0872 (0.0821)	-0.0655 (0.0675)	-0.241*** (0.0888)	0.119 (0.0850)
Constant	-0.425*** (0.114)	-0.531*** (0.126)	-0.414*** (0.0928)	-0.165 (0.504)	1.270** (0.602)	-1.108** (0.531)
Observations	3,245	1,654	1,591	3,245	1,654	1,591
R-squared	0.139	0.197	0.239	0.497	0.496	0.469
Adjusted R-squared	0.127	0.178	0.218	0.431	0.427	0.397
Country Fixed Effects	Yes	Yes	Yes			
Industry Fixed Effects	Yes	Yes	Yes			
Institution Fixed Effects	No	No	No	Yes	Yes	Yes
Year Fixed Effects	Yes	Yes	Yes	Yes	Yes	Yes

Table A.11

Tail climate risks and adaptation measures

This table presents estimates of the effects of tail climate risks on various adaptation measures. Panel A uses $\hat{\beta}_{BMG}$, a dynamic institution-level measure of tail transition risk based on a rolling window of 100 observations, as a measure of climate risk. In columns (1) and (3), IntegratedStrategy is used as the dependent variable. Columns (2) and (4) use DiscussClimateRisk as the dependent variable. Columns (5) and (6) use LogCarbonOffsets and PolicyEngagement as the dependent variables, respectively. Regressions (1), (2), (3), (4) and (6) use a probit model. Regression (5) uses an OLS model. Panel B uses $\hat{\beta}_{VMS}$, a dynamic institution-level measure of tail physical risk (based on a rolling window of 100 observations), as a measure of climate risk. Columns (1), (2), and (3) use a probit model with EnvironmentalTeam, EnvironmentalProducts, and ClimateScenarioAnalysis as the dependent variables, respectively. All regressions use country-year and sector-year fixed effects. Appendix B presents the variable definitions. Standard errors are clustered at the financial institution level and are reported in parentheses. ***, **, and * indicate significance at the 1%, 5% and 10% levels, respectively.

Panel A: Transition risk

VARIABLES	(1) Integrated Strategy	(2) Discuss ClimateRisk	(3) Integrated Strategy	(4) Discuss ClimateRisk	(5) Log CarbonOffsets	(6) Policy Engagement
$\hat{\beta}_{BMG}$ (t-1)	0.225*	0.295**	0.302*	0.387**	0.615	-0.423*
	(0.131)	(0.137)	(0.172)	(0.186)	(0.389)	(0.252)
Beta (t-1)	0.488**	0.133	0.262	0.439	0.876	0.921**
	(0.218)	(0.223)	(0.414)	(0.304)	(0.683)	(0.368)
LogMarketValue (t-1)	0.461***	0.476***	0.320**	0.544***	0.853**	0.429***
	(0.0692)	(0.0648)	(0.155)	(0.132)	(0.354)	(0.137)
Cash (t-1)	0.722	0.528	-3.233	3.399	1.851	5.996***
	(0.882)	(1.060)	(5.530)	(2.946)	(1.706)	(1.938)
NetIncome (t-1)	-2.155	-4.410***	-9.714*	-4.296*	2.612	-0.729
	(1.368)	(1.560)	(5.566)	(2.506)	(2.339)	(2.254)
MtoB (t-1)	-0.0231	-0.126	-0.116	-0.245**	-0.0486	-0.235**
	(0.0777)	(0.0830)	(0.150)	(0.117)	(0.168)	(0.113)
Debt (t-1)	-0.00249	0.00936**	-0.00132	0.0328***	-0.00697	-0.00743
	(0.00428)	(0.00424)	(0.00970)	(0.00802)	(0.0156)	(0.00618)
EnvironmentalTransparencyScore (t-1)			-0.936	2.344***		
			(0.873)	(0.885)		
Constant	-3.180***	-0.745	-0.810	-6.480***	-5.076	-0.836
	(0.558)	(0.649)	(1.185)	(1.208)	(4.074)	(1.166)
Observations	2,016	1,384	581	657	335	812
R-squared					0.620	
Adjusted R-squared					0.338	
Country-Year Fixed Effects	Yes	Yes	Yes	Yes	Yes	Yes
Industry-Year Fixed Effects	Yes	Yes	Yes	Yes	Yes	Yes

Panel B: Physical risk

VARIABLES	(1) Environmental Team	(2) Environmental Products	(3) Climate Scenario Analysis
$\hat{\beta}_{VMS}$ (t-1)	0.131***	0.105***	0.0995*
	(0.0474)	(0.0366)	(0.0510)
Beta (t-1)	0.352	0.246	0.0287
	(0.249)	(0.235)	(0.321)
LogMarketValue (t-1)	0.584***	0.705***	0.541***
	(0.0861)	(0.0854)	(0.100)
Cash (t-1)	1.464	5.543***	1.985
	(1.342)	(1.419)	(1.737)
NetIncome (t-1)	0.154	-2.438	-1.316
	(1.537)	(1.750)	(2.906)
MtoB (t-1)	-0.158**	-0.193**	-0.0438
	(0.0801)	(0.0894)	(0.0922)
Debt (t-1)	0.0117**	0.00610	0.00838
	(0.00466)	(0.00486)	(0.00602)
Constant	-4.356***	-5.783***	-4.395***
	(0.697)	(0.794)	(0.823)
Observations	1,185	1,341	757
Country-Year Fixed Effects	Yes	Yes	Yes
Industry-Year Fixed Effects	Yes	Yes	Yes

Appendix B: Variable description

Table B.1

Risk factor description

VARIABLES	DESCRIPTION
BMG	Transition risk factor, constructed as a long-short portfolio based on both estimated and reported GHG emission intensity data (scopes 1 & 2) for all stocks reported in Refinitiv Eikon and listed on European equity markets (excluding financial sector companies). Alternatively, we build the factor only from Scope 1 reported emission intensities, unscaled emissions, and lagged emissions.
CMA	Difference between the returns on portfolios of low and high investment stocks (Conservative-Minus-Aggressive factor) from Kenneth French website library.
DP	Default premium computed as the spread between the ICE high-yield euro corporate rates against the 3-month Euribor rate (Fred database).
EG	Difference between the returns of portfolios of high and low expected growth stocks (Expected Growth factor) from Hou-Xue-Zhang q-factors data library.
ES	Economic Sentiment indicator from Eurostat database.
HML	Difference between the returns on portfolios of high and low book-to-market stocks (High-Minus-Low factor) from Kenneth French website library.
IA	Difference between the returns on portfolios of high and low investment-to-assets stocks (Investment/Assets factor) from Hou-Xue-Zhang q-factors data library.
LIQ	Nontraded liquidity factor of Pástor and Stambaugh (2003) from https://faculty.chicagobooth.edu/lubos-pastor/data
ME	Difference between the returns on portfolios of small and large stocks from Hou-Xue-Zhang q-factors data library.
MKT	Difference between the returns on the market portfolio and the risk-free rate (Market factor) from Kenneth French website library.
ML	Interbank market liquidity indicator, calculated as the spread between the 3-month Euribor rate against the equivalent Overnight Indexed Swap rate.
NS	North–South spread, computed as the difference between the 10-year German sovereign bond rate against an average of Greece, Ireland, Italy, Spain, and Portugal's 10-year rates (from the European Central Bank Statistical Data Warehouse).
QMJ	Quality-minus-junk (QMJ) factor that invests long quality stocks and short junk stocks (Asness et al., 2019) from the AQR library.
RMW	Difference between the returns of robust and weak stocks (robust-minus-weak factor), based on operational profitability from Kenneth French website library.
ROE	Difference between the returns on portfolios of high and low profitability stocks (Return on Equity factor) from Hou-Xue-Zhang q-factors data library.
RR	Risk Reversal on the USD/EUR options from Bloomberg.
SMB	Difference between the returns on portfolios of small and large stocks (small-minus-big factor) from Kenneth French website library.
VMS	Physical risk factor, constructed as a long-short portfolio based on Trucost physical climate risk scores for all dead and active stocks reported in Refinitiv Eikon and listed on European equity markets (excluding financial sector companies). Alternatively, we use physical climate scores from ISS-ESG and Carbon4Finance.
WML	Difference between the returns on portfolios of the past winner and past loser stocks (momentum factor) from Kenneth French website library.
YC	Yield Curve indicator, computed as the spread between 10-year and 2-year euro area composite rates (from the European Central Bank Statistical Data Warehouse).

Table B.2

Description of financial and extrafinancial firm-level characteristics

VARIABLES	DESCRIPTION
Beta	Equity beta (897E in Datastream).
Board LT incentives	Dummy variable equal to one if board members have long-term compensation incentives (from CGCPDP052 in Refinitiv ESG).
Cash	Ratio of cash (item WC02005 in Worldscope Datastream) to total assets (item WC02999 in Worldscope Datastream).
ClimateScenarioAnalysis	Dummy variable equal to one if the financial institution has conducted a climate scenario analysis for its portfolio of financial assets (CLIMATE_SCENARIO_ANALYSIS in Bloomberg).
Debt	Ratio of total debt to total capital (from Datastream).
DiscussClimateRisk	Dummy variable equal to one if the Management Discussion and Analysis (MD&A) or its equivalent risk section of the financial institution’s annual report discusses business risks related to climate change (CLIMATE_RISKS in Bloomberg).
EnvironmentalTransparency Score	Score measuring the level of disclosure a financial institution offers for the fields under the Environmental Pillar, on a scale of 0 to 1 (ENVIRONMENTAL_PILLAR_DISCLOSURE in Bloomberg).
EnvironmentalProducts	Dummy variable equal to one if the financial institution has at least one product line or service that is designed to have positive effects on the environment (item ENPIDP019 in Datastream).
EnvironmentalTeam	Dummy variable equal to one if the financial institution has an environmental management team (item ENRRDP004 in Datastream).
Institutional ownership	Percentage of ownership by banks, insurance, and pension funds (sum of items S_122, S_128, and S_129 from the Securities Holdings Statistics database)
IntegratedStrategy	Dummy variable equal to one if the financial institution integrates extrafinancial factors in its management discussion and analysis (MD&A) section in the annual report (item CGVSDP018 in Datastream).
LogCarbonOffsets	Natural logarithm of the equivalent of the CO2 offsets, credits, and allowances purchased and/or produced by the financial institution during the year (item in Datastream, expressed in tons).
LogMarketValue	Natural logarithm of market capitalization (item MV in Datastream, expressed in million euros).
LowScope3	Dummy variable equal to one if the financial institution’s Scope3 emissions are in the bottom 10% (from Carbon4Finance).
MtoB	Ratio of market value of equity (item MV in Datastream, expressed in million euros) to book value of equity (item WC03501 in Worldscope Datastream, expressed in thousand euros), multiplied by 1,000.
NetIncome	Ratio of net income (item WC01751 in Worldscope Datastream) to total assets (item WC02999).
PolicyEngagement	Dummy variable equal to one if the financial institution engages with policymakers on possible responses to climate change (from CDP, item CDP_ENG_POLICYMAKERS_CLIMATE_CHG in Bloomberg).
ReductionTargetReached	Dummy variable equal to one if the financial institution has reached or completed an emission reduction target during the year (from CDP, item CDP_EMISS_RED_TGT_REACHED_OR_CP in Bloomberg).
VerifiedScope3	Dummy variable equal to one if all of the financial institution’s Scope 3 emissions have been verified by a third party (from CDP, item CDP_PCT_DATA_VERIFIED_SCOPE_3 in Bloomberg).

Table B.3

Description of country characteristics

VARIABLES	DESCRIPTION
Deaths	Dummy variable equal to one if the financial institution's country projected change in deaths from climate change induced diseases is high (from ND-GAIN, the Notre Dame Global Adaptation Initiative).
ESGmandate	Dummy variable equal to one after the adoption of an ESG disclosure mandate in the financial institution's country, and zero otherwise. From Krueger et al. (2021).
Floods	Projected change in flood hazard in the financial institution's country (from ND-GAIN, the Notre Dame Global Adaptation Initiative).
HighRenewables	Dummy variable equal to one if the financial institution's country is in the top quartile of renewable energy usage. Quartiles are defined in sample each year. From the University of Oxford's Our World in Data platform (item share of primary energy from renewable sources).
LogEmissions	Natural logarithm of the financial institution's country greenhouse gas emissions. From the OECD data platform (Organization for Economic Cooperation and Development).
LowEmissions	Dummy variable equal to one if the financial institution's country is in the bottom quartile of greenhouse gas emissions. Quartiles are defined in sample each year. From the OECD data platform (Organization for Economic Cooperation and Development).
LowEmissionsPerCapita	Dummy variable equal to one if the financial institution's country is in the bottom quartile of greenhouse gas emissions per capita. Quartiles are defined in sample each year. From the OECD data platform (Organization for Economic Cooperation and Development).
WaterDependency	Proportion of the total renewable water resources originated outside the country (from ND-GAIN, the Notre Dame Global Adaptation Initiative).

Table B.4

List of the largest European financial institutions

This table provides a list of financial institutions with a market capitalization of over 10 billion euros on average over the period 2005-2022. Column 4 contains the Datastream identifiers (Symbols).

Name	Sector	Country	Identifier
AIB Group	Banks	Ireland	IE:A5G
Alpha Services and Holdings	Banks	Greece	G:PIST
Banca Monte dei Paschi	Banks	Italy	I:BMPS
Banco Bilbao Vizcaya Argentaria	Banks	Spain	E:BBVA
Banco BPM	Banks	Italy	I:BP
Banco Comercial Portugues 'R'	Banks	Portugal	P:BCP
Banco de Sabadell	Banks	Spain	E:BSAB
Banco Santander	Banks	Spain	E:SAN
Bank of Ireland Group	Banks	Ireland	IE:BIRG
Bank Polska Kasa Opieki	Banks	Poland	PO:PKA
Banque Nationale de Paris Paribas	Banks	France	F:BNP
Barclays	Banks	United Kingdom	BARC
Commerzbank	Banks	Germany	D:CBK
Credit Agricole	Banks	France	F:CRDA
Danske Bank	Banks	Denmark	DK:DAB
Deutsche Bank	Banks	Germany	D:DBK
DNB Bank	Banks	Norway	N:DNB
Erste Group Bank	Banks	Austria	O:ERS
Eurobank Holdings	Banks	Greece	G:EFG
HSBC Holdings	Banks	United Kingdom	HSBA
ING Groep	Banks	Netherlands	H:INGA
Intesa Sanpaolo	Banks	Italy	I:ISP
KBC Group	Banks	Belgium	B:KB
Lloyds Banking Group	Banks	United Kingdom	LLOY
National Bank of Greece	Banks	Greece	G:ETE
Natwest Group	Banks	United Kingdom	NWG
Nordea Bank	Banks	Finland	W:NDAS
OTP Bank	Banks	Hungary	HN:OTP
Piraeus Financial Holdings	Banks	Greece	G:PEIR
PKO Bank	Banks	Poland	PO:PKB
Santander Bank Polska	Banks	Poland	PO:BZW
Skandinaviska Enskilda Banken A	Banks	Sweden	W:SEA
Societe Generale	Banks	France	F:SGE
Standard Chartered	Banks	United Kingdom	STAN
Svenska Handelsbanken A	Banks	Sweden	W:SVK
Swedbank A	Banks	Sweden	W:SWED
Unicredit	Banks	Italy	I:UCG
Credit Suisse Group	Financial Services (Sector)	Switzerland	S:CSGN
Deutsche Boerse	Financial Services (Sector)	Germany	D:DB1

GAM Holding	Financial Services (Sector)	Switzerland	S:GAM
GBL New	Financial Services (Sector)	Belgium	B:GBLN
HAL Trust	Financial Services (Sector)	Netherlands	H:HAT
Investor B	Financial Services (Sector)	Sweden	W:ISBF
Kinnevik B	Financial Services (Sector)	Sweden	W:KIVB
Latour Investment B	Financial Services (Sector)	Sweden	W:LTBF
Man Group	Financial Services (Sector)	United Kingdom	EMG
Mediobanca Banca di Credito Financial	Financial Services (Sector)	Italy	I:MB
Saint James's Place Ordinary	Financial Services (Sector)	United Kingdom	STJ
Schroders	Financial Services (Sector)	United Kingdom	SDR
Sofina	Financial Services (Sector)	Belgium	B:SOF
UBS Group	Financial Services (Sector)	Switzerland	S:UBSG
Aegon	Life Insurance	Netherlands	H:AGN
Ageas (ex-Fortis)	Life Insurance	Belgium	B:AGS
Aviva	Life Insurance	United Kingdom	AV.
CNP Assurances	Life Insurance	France	F:CNP
Legal and General	Life Insurance	United Kingdom	LGEN
Prudential	Life Insurance	United Kingdom	PRU
Swiss Life Holding	Life Insurance	Switzerland	S:SLHN
Admiral Group	Nonlife Insurance	United Kingdom	ADM
Allianz	Nonlife Insurance	Germany	D:ALV
Assicurazioni Generali	Nonlife Insurance	Italy	I:G
AXA	Nonlife Insurance	France	F:MIDI
Hannover Rueck	Nonlife Insurance	Germany	D:HNR1
Mapfre	Nonlife Insurance	Spain	E:MAP
Muenchener Rückversicherung	Nonlife Insurance	Germany	D:MUV2
Sampo 'A'	Nonlife Insurance	Finland	M:SAMA
Swiss Re	Nonlife Insurance	Switzerland	S:SREN
Zurich Insurance Group	Nonlife Insurance	Switzerland	S:ZURN
Fastighets Balder B	Real Estate Investment and Services	Sweden	W:BALB
British Land	Real Estate Investment Trusts	United Kingdom	BLND
Klepierre REIT	Real Estate Investment Trusts	France	F:LI
Land Securities Group	Real Estate Investment Trusts	United Kingdom	LAND
Segro	Real Estate Investment Trusts	United Kingdom	SGRO
Unibail Rodamco We Stapled Units	Real Estate Investment Trusts	France	H:UBL

Appendix C: VaR estimation

Our approach requires estimating the VaR of financial institutions, which in turn are used as inputs in a correlation matrix to assess tail risk dependence. In existing articles, asset comovements are estimated based on returns, volatility, and VaR (e.g., Diebold and Yilmaz, 2009; Adams et al., 2014; White et al., 2015). Table OA.1 shows that the interconnections between financial institutions are different if we use returns or the VaR to estimate comovements. To capture systemic risk, measuring comovements among tail risk indicators seems better suited than relying on return comovements.

The VaR is the estimated loss of a financial institution that, within a given period, is not exceeded with a certain probability θ. Thus, if θ is equal to 95%, the 1-month θ-VaR shows a negative return that is not exceeded in this month with a 95% probability (Equation A.1). While the choice of 95% VaR is common in the literature, the main conclusions of this study remain unchanged when different probability values are used. Nor are the conclusions affected by the use of an expected shortfall measure, instead of the VaR, derived from the same GARCH model.

$$prob[return_t < -VaR_t | \Psi_t] = \theta \tag{A.1}$$

where Ψ_t is the information set available at time *t*. The VaR can be estimated dynamically based on Equation (A.2):

$$VaR_{i,t} = \hat{\mu}_{i,t} + \hat{\sigma}_{i,t|t-1} F(1-\theta)^{-1} \tag{A.2}$$

where $\hat{\sigma}_{i,t|t-1}$ is the conditional standard deviation given the information at $t-1$, F^{-1} is the inverse probability density function of a prespecified distribution and where $\hat{\mu}_{i,t}$ is the mean return of institution *i* at time *t*. For simplicity, $\hat{\mu}_{i,t}$ is estimated using the overall sample mean instead of a rolling window, as its effect on the overall variation in the VaR is very limited.

Following Kuester et al. (2006), we model $\hat{\sigma}_{i,t}$ by extracting the conditional standard deviation from a GARCH model. This procedure captures the time-varying volatility of returns and significantly improves the responsiveness of the VaR to shifts in the return process. For most of our return series, we empirically observe that negative returns at time $t-1$ affect the variance at time t more strongly than do positive returns. To reflect this leverage effect, we apply the threshold GARCH model of Glosten et al. (1993) presented in Equation (A.3). This is the simplest asymmetric GARCH specification, which seems appropriate given the moderate size of our sample. We confirm that the parameter γ in Equation (A.3) is positive for 286 financial institutions and positive and significant at the 5% level for 107 out of 371 series.

$$\hat{\sigma}_{i,t}^2 = \omega + (\alpha + \gamma \mathbb{I}_{t-1})\varepsilon_{t-1}^2 + \beta \hat{\sigma}_{i,t-1}^2 \tag{A.3}$$

$$\mathbb{I}_{t-1} = \begin{cases} 0, & r_{t-1} < \mu \\ 1, & r_{t-1} \geq \mu \end{cases}$$

All the parameters (μ, ω, α, γ, and β) are estimated simultaneously by maximizing the log likelihood. Since the sample size is moderate and we are not directly interested in the model's forecasting ability in this study, we estimate only the in-sample VaR.

Table C.1 shows the ability of our model to fit the data and capture tail risk. We present the Akaike, Bayes, Shibata, and Hannan Quinn information criteria for various model specifications and error distribution assumptions (Panel A). We show that the GJR-GARCH model of Glosten et al. (1993) fits the data best compared with alternatives. This finding is consistent with the work of Brownlees et al. (2011), which shows that the GJR-GARCH model works best in forecasting stock volatility. Since we are primarily interested in tail risk measurement, we now turn our attention to the results of the VaR exceedance tests presented in Panel B. The unconditional coverage test of Kupiec (1995) assesses whether the observed frequency of VaR exceedances is consistent with expected exceedances. The conditional coverage test of Christoffersen et al. (2001) complements the previous test by considering the potential dependence between the occurrences of exceedances. Finally, the test of Christoffersen and Pelletier (2004) focuses on the duration between the VaR exceedances. We show that the GJR-GARCH model seems appropriate for reflecting the level of tail risk of financial institutions.[30] Interestingly, although the skew-normal distribution is not the best fit for the distribution of the data as a whole (Panel A), it is more effective than most other distributions in fitting tail behavior (Panel B). In particular, the skew-normal distribution is associated with the lowest standard deviation around the expected number of exceedances for our sample of return series. The distribution also leads to the lowest number of rejections in the Kupiec (1995) and Christoffersen et al. (2001) tests. Our finding is in line with Brownlees et al. (2011), who mention that despite the prevalence of fat-tailed financial returns, they find no advantage in using a heavier-tailed error distribution. We also show in Table C.2 that our results are robust to the use of the GARCH and CS-GARCH models instead of the GJR-GARCH model and to other error distribution assumptions, specifically, Student's and generalized errors.

[30] A potential alternative is the component GARCH of Engle and Lee (1999).

Table C.1

Model selection

This table presents diagnostic tests for model selection and error distribution assumptions (see Equation A.3). Panel A reports the Akaike, Bayes, Shibata, and Hannan Quinn information criteria. Panel B reports the results from the following VaR exceedance tests: the UC test of Kupiec (1995), the CC test of Christoffersen et al. (2001), and the Duration test of Christoffersen and Pelletier (2004). Panel B also indicates the expected number of VaR exceedances, the average realized number of VaR exceedances, and the standard deviation of the difference between the realized and expected number of VaR exceedances. GJR-GARCH and CS-GARCH represent the models of Glosten et al. (1993) and the component GARCH of Engle and Lee (1999), respectively.

Panel A: Information criteria

Model	Error distribution	Akaike	Bayes	Shibata	Hannan Quinn
	Skew-normal	7.032	7.128	7.030	7.071
GJR-GARCH	Student	**6.946**	**7.043**	**6.945**	**6.985**
	Generalized error	6.953	7.049	6.951	6.992
GARCH		7.065	7.145	7.064	7.097
GJR-GARCH	Skew-normal	**7.032**	**7.128**	**7.030**	**7.071**
CS-GARCH		7.081	7.193	7.079	7.126

Panel B: VaR exceedance tests

Model	Error distribution	Expected VaR 5% exceed	Realized VaR 5% exceed	Standard deviation (Realized-Expected)	Number of rejections		
					VaR UC test	VaR CC test	VaR Duration test
	Skew-normal	10	9.66	**5.29**	**5**	**5**	10
GJR-GARCH	Student	10	11.06	9.70	7	11	11
	Generalized error	10	**9.94**	8.75	10	10	**9**
GARCH		10	**9.83**	5.54	**4**	15	**9**
GJR-GARCH	Skew-normal	10	9.66	**5.29**	5	**5**	10
CS-GARCH		10	10,20	7.36	8	15	**9**

Table C.2

Alternative GARCH models and error distributions

This table presents the determinants of systemic risk based on the time series analysis described in Equation (7). We use Ω_1, the systemic risk measure derived from the first principal component defined in Equation (3), as the dependent variable. The independent variables are the ΔVaR of the risk factors, as described in Section 2.5, except for RR and ES, which are in first differences. In specifications 1-3, the VaR is estimated with a GJR-GARCH model with skewed normal, student, and generalized error distributions, respectively. In specifications 4-5, the VaR is estimated with a GARCH model with a skewed normal distribution and a CS-GARCH model with a skewed normal distribution. Newey–West standard errors are reported in parentheses. ***, **, and * indicate significance at the 1%, 5% and 10% levels, respectively. Standardized regression coefficients are reported. A positive coefficient always indicates that a degradation in the indicator is associated with an increase in systemic risk.

VARIABLES	(1) Ω_1	(2) Ω_1	(3) Ω_1	(4) Ω_1	(5) Ω_1
BMG	0.062*	0.067*	0.068*	0.069**	0.076**
	(0.036)	(0.039)	(0.039)	(0.032)	(0.033)
VMS	0.008	0.009	0.003	0.075	0.091
	(0.027)	(0.026)	(0.026)	(0.071)	(0.071)
MKT	0.313***	0.282***	0.315***	0.453***	0.382***
	(0.091)	(0.090)	(0.091)	(0.125)	(0.109)
ML	0.033	0.038	0.036	0.054	0.065
	(0.050)	(0.042)	(0.048)	(0.057)	(0.056)
DP	0.275***	0.315***	0.296***	0.123	0.178
	(0.085)	(0.080)	(0.085)	(0.119)	(0.113)
YC	0.011	-0.015	-0.008	0.0003	0.003
	(0.024)	(0.024)	(0.025)	(0.031)	(0.036)
NS	0.031	0.036	0.033	0.025	0.040
	(0.027)	(0.024)	(0.024)	(0.029)	(0.033)
RR	-0.059	-0.062*	-0.056	-0.061	-0.064*
	(0.036)	(0.035)	(0.035)	(0.043)	(0.038)
ES	0.496***	0.484***	0.474***	0.438***	0.449***
	(0.062)	(0.063)	(0.058)	(0.082)	(0.079)
Constant	0	0	0	0	0
	(0.026)	(0.025)	(0.024)	(0.026)	(0.026)
Observations	207	207	207	207	207
R-squared	0.864	0.868	0.867	0.779	0.738
Adjusted R-squared	0.858	0.862	0.861	0.769	0.726

Appendix D: Climate risk factors

Factor analysis

The cumulative returns of our “nontail” climate risk factors are plotted in Figure D.1. We observe that the transition and physical risk factors underperformed over time. While risk factors generally have a positive long-term mean return (risk premia), this underperformance may be due to the occurrence of unexpected climate shocks over the past decade, which are likely to have a negative impact on brown assets (Pástor et al., 2021). The cumulative returns of our transition risk factor are in line with other articles in the literature (e.g., Pástor et al., 2022). The trend is more pronounced for our transition risk factor than for our physical risk factor. The transition risk factor shows an annualized return of -2.4% over the period 2005–2022 with a t statistic of -1.16, whereas the physical risk factor displays an annualized return of -1.2% with a t statistic of -0.80.

Next, we examine how our transition and physical risk factors react to exogenous climate shocks. For transition risk, we rely on the Google search volume on the topic of climate change. We compute the monthly arithmetic average of the search volume in the three and five most represented countries in our study (France, the United Kingdom, and Switzerland are in the top three; the top five additionally includes Germany and Sweden). Like Choi et al. (2020), we then regress the log monthly change in Google searches on month fixed effects. The residuals of this regression constitute our variable *Abnormal Google Search Climate Change*, an empirical proxy of climate change concerns. For physical risk, we rely on the monthly damage associated with climate-related natural disasters in Europe from the International Disaster Database (EM-DAT). The damage provided by EM-DAT is expressed in US dollars and adjusted for inflation. We use the natural logarithm of the monthly damage, as well as a dummy variable equal to one if the monthly damage is above a certain threshold (500 million). Our findings are reported in

Table D.1. In Panel A, we show that the transition risk factor returns negatively correlate with Google search volume on climate change in the top three countries (columns 1 to 4) and top five countries (columns 5 to 8). We turn to physical risk in Panel B and show a negative correlation between the returns of the physical risk factor and the log monthly climate-related damage (columns 1 to 4), as well as our dummy variables equal to one when Europe is hit by large climate-related disasters (columns 5 to 8). In unreported tests, we use various alternative thresholds for defining large climate-related disasters (100 million, 200 million, and 1 billion) and find that the physical risk factor shows a stronger negative reaction as the damage threshold increases. Overall, these findings highlight that our climate risk factors capture a wide range of climate-related shocks that affect the value of nonfinancial companies. Importantly, similar to the findings reported elsewhere in this article, these results hold after controlling for a wide set of factors. In unreported tests, we also conduct placebo tests by regressing the contemporaneous value of our factors on the future values of the climate indicators (forward values at 2, 3, and 6 months). As expected, these placebo tests all yield insignificant results.

Next, we assess whether climate risks are reflected in the prices of nonfinancial equity. To this end, we divide the sample of nonfinancial equities into ten value-weighted portfolios, based on quantiles of GHG emission intensities and physical risk scores. We regress each portfolio's returns on the transition and physical risk factors, as well as on the Fama and French (2015) factors. If climate risks are embedded in asset prices, we expect the portfolio returns of companies with high (low) GHG intensity or physical risk scores to be positively (negatively) and significantly related to the respective climate risk factors. The test is applicable mainly to portfolios that are not used to construct climate risk factors. Therefore, to improve the relevance of the test, we use climate risk factors based on deciles ("10-1" spread) rather than quintiles. The results are presented in Table OA.11 (Online Appendix). Overall, we find evidence that transition risk is accounted for in the time series of nonfinancial equity returns. In contrast, there is no such evidence for physical risk.

Table D.2 shows the characteristics of the climate factor constituents. We present the information pertaining to the transition risk factor, BMG, in Panel A. As of 2022, the BMG factor comprises 410 brown firms and 410 green firms. We observe sectoral concentration in both the long and short portfolio allocations. For example, firms from the personal goods and software industries, two low-emitting sectors, are most represented in the green portfolio, whereas companies from the oil and gas production industry, a very GHG-intensive sector, are most often found in the brown portfolio. Despite this concentration, the portfolios remain invested in all sectors, suggesting that our transition risk factor is well suited to capturing both the sectoral and company-level effects of transition climate risk.

The information on the physical risk factor, VMS, is available in Panel B. As of 2022, the VMS factor comprises 419 firms that are vulnerable to physical risk and 440 firms that are deemed safe. The vulnerable and safe portfolios have average physical risk scores of 62.4 and 32.0, respectively.[31] Overall, we find that the physical risk factor is better diversified across sectors than the transition risk factor.

Factor robustness

To alleviate the concern that our main conclusions in the rest of the article may depend on the specification of our climate risk factors, we evaluate the robustness of our key results on alternative climate risk factors. For transition risk, we construct alternative BMG factors using unscaled scope 1 and 2 GHG emissions (in line with Bolton and Kacperczyk, 2021) rather than

[31] This score goes from 0 (extremely low risk) to 100 (extremely high risk). When considering the totality of European firms covered by Trucost, the median Composite Moderate 2050 score is 49, while the 25th (75th) percentile equals 39 (57).

GHG intensities, 12-month lagged emission intensities (in line with Zhang, 2024) to account for the lag in GHG emission reporting, reported GHG emission intensities only (in line with Aswani et al, 2024) and by sorting companies by emission deciles ('10-1' spread) rather than quintiles. We find that the correlation between the alternative BMG factors is high and that our main results remain unchanged regardless of the BMG factor considered (see Table D.3). This contrasts with the literature on the carbon premium, which finds divergent results depending on the type of GHG emissions under consideration. Conversely, it seems that the effect of GHG emissions on market risk and covariations is robust to the different specifications of the BMG factor.

Regarding physical risk, as an alternative to using Trucost's physical risk score, we construct two factors on the basis of the physical risk scores from Carbon4Finance and ISS-ESG[32]. The average correlation between the three factors is relatively low (27%), highlighting the existence of significant disagreement on the exposure of nonfinancial firms to physical risk (see also Hain et al., 2022). The difference in firm coverage across data providers may also mechanically reduce the correlation between the factors. However, our main results are robust to the various physical risk factor specifications (see Table D.3). In all the cases, we find no evidence that physical risk has significant effects on systemic risk in the financial sector. In addition to the fact that investors appear to view physical risk as long-term risk (Stroebel and Wurgler, 2021), the lack of results may be explained by the disagreement between physical risk scores. Such a mismatch may create dispersion in investment flows in the event of a natural disaster, limiting or delaying the incorporation of physical risk into asset prices. This effect is examined by Billio et al. (2021) for ESG scores.

[32] The physical score of ISS-ESG represents the fraction of each issuer value susceptible of being lost due to physical climate risk by 2050 in a likely climate-change scenario.

The brown portfolio of the transition risk factor and the vulnerable portfolio of the physical risk factor are overweight in the oil and gas sector (26.8% and 11.0%, respectively; see Table D.2). Although this industry bias is an important feature for capturing the impact of climate shocks on nonfinancial companies, we recognize that it may also make factors sensitive to nonclimate events, such as oil shocks. We perform two tests to check the robustness of our results to this industry bias. In a first unreported test, we construct an alternative set of climate risk factors that excludes firms in the oil and gas sector (i.e., oil and gas producers and oil equipment and services). We then reestimate the regressions in Equation (7) with this new transition risk factor and obtain results similar to those in Table A.4. The second test consists of controlling for log returns on the Brent price in Equation (7) and the sensitivity of each financial institution to oil price returns in Equation (9). We present the results in Tables OA.2 and OA.5 (Online Appendix), which show quantitatively similar results to those in Tables A.4 and A.5.

Finally, to alleviate the risk that our climate risk factors capture nonclimate-related characteristics, we conduct a placebo test. The purpose of the test is to examine whether climate risk factors significantly influence systemic risk in the financial sector over the period 1990–2005. Investors' awareness of climate change was limited at the time, and climate data on GHG emissions and physical risk scores were almost nonexistent. As a result, we do not expect the returns of financial institutions to reflect climate risks over the selected period, but the noise of the factors could affect the results. To perform this exercise, we download data for financial and nonfinancial equities from 1990 to 2005. We then reconstruct the climate risk factors based on the returns of nonfinancial firms from 1990 to 2005. To construct the long and short portfolios, we use the average GHG emission intensity for each firm from 2005 to 2022 and the 2022 physical risk scores. The results are reported in Table OA.12 (Online Appendix). As expected, we find no positive and significant impact of transition or physical climate risk on systemic risk in the European financial sector over the period 1990–2005.

Figure D.1

Cumulative returns of climate risk factors

This figure represents the cumulative returns of the transition and physical risk factors (January 2005 = 100), built based on Equations (4) and (5).

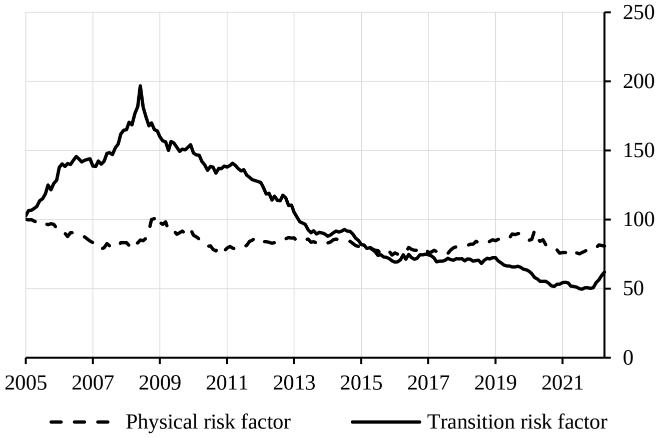


Table D.1

Climate risk factors and climate shocks

This table presents the associations between climate risk factors and climate shocks.

Panel A reports the associations between BMG, the transition risk factor, and climate news indicators. Columns (1) to (4) use the abnormal Google search volume for the topic "climate change" in the 3 most represented countries in our sample of financial institutions (France, the United Kingdom, and Switzerland). Columns (5) to (8) use the abnormal Google search volume for the topic "climate change" in the 5 most represented countries in our sample of financial institutions (France, Germany, the United Kingdom, Sweden, and Switzerland). The independent variables are the first differences or returns of the "nontail" risk factors, as described in Section 2.5. Newey–West standard errors are reported in parentheses. ***, **, and * indicate significance at the 1%, 5% and 10% levels, respectively.

Panel A: Transition risk factor

VARIABLES	(1) BMG	(2) BMG	(3) BMG	(4) BMG	(5) BMG	(6) BMG	(7) BMG	(8) BMG
	Google Search Volume Top 3 countries				Google Search Volume Top 5 countries			
Abnormal Google Search Climate Change (t-1)	-1.728*	-1.611**	-1.649**	-2.022**	-1.654	-1.468*	-1.550*	-1.923**
	(1.015)	(0.794)	(0.824)	(0.784)	(1.001)	(0.763)	(0.806)	(0.777)
MKT	0.0556	-0.0149	-0.0139	0.000645	0.0556	-0.0152	-0.0141	0.00105
	(0.0343)	(0.0356)	(0.0361)	(0.0359)	(0.0344)	(0.0359)	(0.0363)	(0.0361)
ML	2.254		2.048	2.321	2.337		2.130	2.424
	(2.267)		(2.415)	(2.108)	(2.284)		(2.435)	(2.134)
DP	-0.0173		-0.0105	0.0809	-0.0180		-0.0101	0.0797
	(0.194)		(0.205)	(0.185)	(0.195)		(0.205)	(0.186)
YC	0.0527		0.119	-0.0910	0.0585		0.125	-0.0840
	(0.242)		(0.251)	(0.273)	(0.242)		(0.251)	(0.272)
NS	-0.0951		-0.0360	-0.0428	-0.0883		-0.0293	-0.0346
	(0.405)		(0.411)	(0.407)	(0.407)		(0.411)	(0.409)
RR	-0.0510		-0.0369	-0.0281	-0.0518		-0.0379	-0.0282
	(0.365)		(0.336)	(0.313)	(0.366)		(0.337)	(0.314)
ES	0.0435		0.0322	0.0329	0.0449		0.0333	0.0343
	(0.0550)		(0.0335)	(0.0352)	(0.0551)		(0.0340)	(0.0356)
SMB		-0.101	-0.0879	-0.0562		-0.0999	-0.0856	-0.0527
		(0.0957)	(0.103)	(0.101)		(0.0964)	(0.104)	(0.103)
HML		0.348***	0.348***	0.737***		0.348***	0.348***	0.732***
		(0.0692)	(0.0710)	(0.161)		(0.0697)	(0.0714)	(0.162)
RMW				0.437***				0.436***
				(0.159)				(0.159)
CMA				-0.108				-0.102
				(0.176)				(0.176)
WML				0.210***				0.208***
				(0.0746)				(0.0746)
Constant	-0.261	-0.180	-0.182	-0.491***	-0.260	-0.178	-0.181	-0.488***
	(0.187)	(0.173)	(0.174)	(0.169)	(0.188)	(0.174)	(0.174)	(0.171)
Observations	207	207	207	207	207	207	207	207
R-squared	0.037	0.149	0.157	0.238	0.035	0.146	0.154	0.234
Adjusted R-squared	-0.002	0.133	0.114	0.189	-0.005	0.129	0.111	0.183

Panel B reports the associations between VMS, the physical risk factor, and climate event indicators obtained from EM-DAT. Columns (1) to (4) use the natural logarithm of the monthly damage from climatic disasters in Europe. Columns (5) to (8) use a dummy variable equal to one if the monthly damage from climatic disasters in Europe is above USD 500 million. The independent variables are the first differences or returns of the "nontail" risk factors, as described in Section 2.5. Newey–West standard errors are reported in parentheses. ***, **, and * indicate significance at the 1%, 5% and 10% levels, respectively.

Panel B: Physical risk factor

VARIABLES	(1) VMS	(2) VMS	(3) VMS	(4) VMS	(5) VMS	(6) VMS	(7) VMS	(8) VMS
Log DisasterDamages (t-1)	-0.0564**	-0.0520**	-0.0534**	-0.0427*				
	(0.0232)	(0.0260)	(0.0262)	(0.0255)				
Disasters Above500Mil (t-1)					-1.058**	-1.140**	-1.124**	-0.947*
					(0.429)	(0.473)	(0.495)	(0.484)
MKT	-0.0634*	-0.0731***	-0.0760***	-0.0339	-0.0648*	-0.0746***	-0.0772***	-0.0358
	(0.0351)	(0.0281)	(0.0291)	(0.0304)	(0.0349)	(0.0278)	(0.0288)	(0.0302)
ML	1.724		0.852	0.938	1.742		0.879	0.982
	(1.658)		(1.310)	(1.295)	(1.659)		(1.292)	(1.287)
DP	-0.0118		-0.141	-0.201*	-0.00219		-0.137	-0.195*
	(0.124)		(0.103)	(0.110)	(0.122)		(0.102)	(0.110)
YC	-0.192		-0.119	-0.170	-0.178		-0.0982	-0.154
	(0.123)		(0.115)	(0.128)	(0.122)		(0.111)	(0.124)
NS	-0.280		-0.272	-0.280	-0.263		-0.247	-0.259
	(0.359)		(0.314)	(0.304)	(0.359)		(0.310)	(0.301)
RR	-0.363		-0.163	-0.0350	-0.353		-0.146	-0.0214
	(0.323)		(0.279)	(0.257)	(0.324)		(0.277)	(0.256)
ES	0.0325		0.0267	0.0186	0.0313		0.0261	0.0186
	(0.0473)		(0.0292)	(0.0255)	(0.0486)		(0.0302)	(0.0264)
SMB		-0.391***	-0.399***	-0.346***		-0.398***	-0.406***	-0.351***
		(0.0727)	(0.0757)	(0.0747)		(0.0717)	(0.0752)	(0.0745)
HML		0.116**	0.109**	-0.0383		0.113**	0.107**	-0.0300
		(0.0496)	(0.0495)	(0.0887)		(0.0488)	(0.0490)	(0.0886)
RMW				0.107				0.120
				(0.123)				(0.122)
CMA				0.390***				0.383***
				(0.115)				(0.114)
WML				-0.0637				-0.0620
				(0.0542)				(0.0538)
Constant	-0.00111	0.0696	0.0745	0.0459	-0.0155	0.0662	0.0683	0.0383
	(0.126)	(0.111)	(0.112)	(0.120)	(0.123)	(0.107)	(0.109)	(0.117)
Observations	207	207	207	207	207	207	207	207
R-squared	0.075	0.237	0.252	0.303	0.078	0.244	0.258	0.308
Adjusted R-squared	0.038	0.221	0.214	0.256	0.040	0.229	0.220	0.262

Table D.2

Sectoral breakdown of assets constituting climate risk factors

This table presents the summary statistics of the climate risk factor constituents.

Panel A presents descriptive statistics for the assets constituting the transition risk factor in 2022. The transition risk factor is constructed as a long–short portfolio based on GHG emission intensity (scopes 1 & 2) for all dead and alive stocks listed on European equity markets (excluding financial sector companies). The portfolio is long for high-climate-risk firms (>80th percentile) and short for low-climate-risk firms (<20th percentile).

Panel A: Transition risk factor

Sectors	Number of firms		% in portfolio		Average GHG intensity (Ratio of scope 1 & 2 emissions to sales)	
	Low climate risk	High climate risk	Low climate risk	High climate risk	Low climate risk	High climate risk
Aerospace and Def.	1	1	0.0%	0.2%	0.42%	655%
Alternative Energy	5	6	0.6%	0.1%	0.27%	1,105%
Automobiles		3		0.2%		22%
Beverages	1	1	0.1%	0.0%	0.02%	15%
Chemicals	1	27	0.3%	7.5%	0.34%	65%
Construction and Mat.	7	15	0.1%	2.2%	0.34%	145%
Electricity	3	31	0.1%	14.1%	0.10%	147%
Electronic Equipment	7	1	0.2%	0.1%	0.39%	41%
Fixed Line Telecom.	7	6	1.5%	0.6%	0.30%	40%
Food and Drug Retail	6		1.0%		0.27%	
Food Producers		19		2.2%		610%
Forestry and Paper	1	14	0.0%	1.7%	0.00%	59%
Gas, Water	1	12	0.0%	7.4%	0.51%	118%
General Industrials	2	18	0.3%	1.9%	0.49%	52%
General Retailers	38	2	4.8%	0.0%	0.27%	21%
Health Care	12	5	1.7%	0.6%	0.29%	38%
Household Goods	9	2	0.7%	0.1%	0.31%	27%
Industrial Engineering	3	2	0.6%	0.1%	0.35%	33%
Metals and Mining		19		2.7%		12,425%
Industrial Transport.	6	28	1.4%	3.8%	0.34%	181%
Leisure Goods	4		0.2%		0.24%	
Media	33	1	5.8%	1.3%	0.29%	37%
Mining		35		13.4%		2,424%
Oil and Gas Prod.		41		24.9%		121%
Oil Equipment	2	18	0.2%	1.9%	0.10%	113%
Personal Goods	13	3	25.5%	0.1%	0.29%	29%
Pharmaceuticals	12	9	9.4%	1.9%	0.22%	62%
Software	105	4	15.5%	0.1%	0.31%	1,138%
Support Services	22	6	1.9%	0.4%	0.23%	53%
Technology Hardware	14	3	2.2%	0.1%	0.27%	34%
Travel and Leisure	15	30	1.9%	3.4%	0.25%	105%
Unclassified	80	48	24.1%	7.2%	0.26%	204%
Total	410	410	100%	100%	0.28%	934%

Panel B presents descriptive statistics for the assets constituting the physical risk factor in 2022. The physical risk factor is constructed as a long–short portfolio based on Trucost physical risk scores for all dead and alive stocks listed on European equity markets (excluding financial sector companies). The portfolio is long for high-climate-risk firms (>80th percentile) and short for low-climate-risk firms (<20th percentile).

Panel B: Physical risk factor

Sector	Number of stocks		% of portfolio		Average physical score (moderate 2050)	
	Low climate risk	High climate risk	Low climate risk	High climate risk	Low climate risk	High climate risk
Aerospace and Def.	2	7	0.9%	1.5%	30.5	61.9
Alternative Energy	4	6	0.6%	0.0%	34.5	67.3
Automobiles	6	2	1.2%	0.0%	33.0	71.0
Beverages	8	3	2.6%	0.7%	33.1	62.0
Chemicals	7	10	0.9%	4.2%	33.6	62.2
Construction and Mat.	18	16	2.4%	1.1%	33.0	61.6
Electricity	5	2	0.3%	0.7%	31.8	62.0
Electronic Equipment	5	3	1.0%	0.0%	31.0	68.0
Fixed Line Telecom.	4	5	2.0%	1.2%	28.5	60.6
Food and Drug Retail	4	3	1.7%	0.1%	32.8	62.7
Food Producers	18	15	6.9%	0.5%	31.8	64.3
Forestry and Paper	5	3	2.5%	0.2%	32.4	61.3
Gas, Water		3		0.4%		62.7
General Industrials	13	11	1.2%	1.0%	32.2	63.5
General Retailers	21	6	5.8%	0.0%	32.7	61.3
Health Care	17	11	4.1%	3.4%	32.8	60.2
Household Goods	16	7	3.6%	0.4%	33.0	61.9
Industrial Engineering	12	6	3.0%	0.6%	33.5	62.7
Metals and Mining	7	4	0.8%	0.1%	30.4	63.0
Industrial Transport.	15	16	14.6%	4.1%	32.7	64.4
Leisure Goods	6	5	0.2%	0.3%	31.8	62.0
Media	4	24	0.1%	4.1%	29.8	62.1
Mining	15	21	0.3%	0.1%	31.7	63.0
Oil and Gas Prod.	11	9	2.9%	10.8%	33.0	64.0
Oil Equipment	7	6	0.4%	0.2%	30.3	65.7
Personal Goods	3	7	1.0%	0.5%	35.0	64.3
Pharmaceuticals	39	25	7.4%	12.3%	31.3	62.2
Software	31	37	4.3%	7.8%	30.8	61.1
Support Services	11	16	1.7%	4.3%	33.9	62.0
Technology Hardware	25	16	2.2%	3.9%	32.1	61.8
Travel and Leisure	12	22	5.9%	2.4%	32.1	61.2
Unclassified	89	92	17.2%	32.9%	31.2	62.1
Total	440	419	100%	100%	32.0	62.4

Table D.3

Determinants of systemic risk—alternative climate risk factors

This table presents the determinants of systemic risk based on the time series analysis described in Equation (7). We use Ω_1, the systemic risk measure derived from the first principal component defined in Equation (3), as the dependent variable. The control variables are consistent with specification (1) in Table A.4. BMG corresponds to the transition risk factor described in Section 2.2, BMG (quantile 90) focuses on deciles ("10-1" spread) rather than quintiles, BMG (lagged emissions) uses emission intensities lagged by 12 months to account for the lag in GHG emissions reporting, BMG (reported emissions) only accounts for emissions reported by companies and ignores estimates, and BMG (unscaled emissions) focuses on absolute GHG emissions rather than GHG intensities. VMS represents the physical risk factor described in Section 2.2, VMS (quantile 90) focuses on deciles ("10-1" spread) rather than quintiles, VMS (C4F score) uses the physical risk scores provided by Carbon4Finance, and VMS (ISS score) uses the physical risk scores provided by ISS-ESG. Newey–West standard errors are reported in parentheses. ***, **, and * indicate significance at the 1%, 5% and 10% levels, respectively. Standardized regression coefficients are reported. A positive coefficient always indicates that a degradation in the indicator is associated with an increase in systemic risk.

VARIABLES	(1) Ω_1	(2) Ω_1	(3) Ω_1	(4) Ω_1	(5) Ω_1	(6) Ω_1	(7) Ω_1	(8) Ω_1	(9) Ω_1
BMG	0.061* (0.036)								
BMG (quantile 90)		0.061* (0.033)							
BMG (lagged emissions)			0.063* (0.035)						
BMG (reported emissions)				0.074** (0.035)					
BMG (unscaled emissions)					0.078* (0.046)				
VMS						0.005 (0.028)			
VMS (quantile 90)							-0.009 (0.022)		
VMS (C4F score)								0.002 (0.046)	
VMS (ISS score)									-0.052 (0.053)
Observations	207	207	195	207	207	207	207	207	207
Controls	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes
R-squared	0.864	0.864	0.865	0.865	0.866	0.860	0.860	0.860	0.862
Adjusted R-squared	0.858	0.858	0.860	0.860	0.860	0.854	0.854	0.854	0.856

Appendix E: Climate exposure CoVaR indicator

The construction of climate risk indicators is essential for policymakers and stakeholders to quantify and monitor the potential losses associated with the transition and physical risks within the financial sector over time. The framework described in Section 2 is well suited for statistically analyzing the effects of extreme climate risks on financial stability ex ante, particularly under conditions of uncertainty regarding the pricing of brown and green assets. However, the filters applied to the series in Section 2 limit the ability to derive dynamic climate risk indicators that quantify the magnitude of the effect of climate shocks on financial institutions.

In this Appendix, we introduce the C-CoVaR indicator, building on the methodology described in Section 2 and on the work of Adrian and Brunnermeier (2016). This indicator is based on a system of two quantile regressions, which allows us to distinguish between the first- and second-round effects of climate shocks on financial institutions. By leveraging quantile regressions, it also provides a robustness check for the main results of the paper.

We define Ω_1' as the first principal component extracted from the stock returns of financial institutions. This variable captures return comovements within the financial institution system. Using quantile regression, we first estimate the sensitivity of Ω_1' to climate risk factors:

$$\Omega_{1,t}' = \alpha_q^{\Omega_1'} + \beta_{q,t}^{(\Omega_1'|f)} f_t + \beta_{q,t}^{(\Omega_1'|g)} g_t + \varepsilon_{q,t}^{\Omega_1'} \qquad \text{(E.1)}$$

where f represents the nontail climate risk factors and g represents a set of macroeconomic and financial control variables. $\beta_{q,t}^{(\Omega_1'|f)}$ captures the sensitivity of extreme negative comovements among financial institutions to climate-related shocks.

Next, for each financial institution i, we estimate the following quantile regression:

$$R_t^i = \alpha_q^i + \beta_{q,t}^{(i|f)} f_t + \beta_{q,t}^{(i|g)} g_t + \beta_{q,t}^{(i|\Omega_1')} \Omega_{1,t}' + \varepsilon_{q,t}^i \tag{E.2}$$

In this model, $\beta_{q,t}^{(i|f)}$ measures the direct (first-round) impact of climate risks on the returns of institution *i*. $\beta_{q,t}^{(i|\Omega_1)}$ captures the exposure of financial institution *i* to the remaining financial sector, representing systemic risk exposure. This coefficient is related to $X_{1,i}$ (Equation 4) after controlling for the influence of other risk factors on each financial institution. By combining $\beta_{q,t}^{(\Omega_1'|f)}$ from Equation (E.1) and $\beta_{q,t}^{(i|\Omega_1')}$ from Equation (E.2), we can estimate the second-round effect of climate shocks on financial institutions.

To assess the financial implications of extreme climate shocks, we estimate the dynamic VaR of the climate risk factors ($VaR_{q,t}^f$), following the approach detailed in Appendix C, and calculate their marginal effect on each financial institution and the broader system:

$$VaR_{q,t}^{(\Omega_1'|VaR_q^f)} = \beta_{q,t}^{(\Omega_1'|f)} VaR_{q,t}^f \tag{E.3}$$

$$VaR_t^{(i|VaR_q^f)} = \beta_{q,t}^{(i|f)} VaR_{q,t}^f + \beta_{q,t}^{(i|\Omega_1')} VaR_{q,t}^{(\Omega_1'|VaR_q^f)} \tag{E.4}$$

Our individual C-CoVaR indicator is given by Equation E.4. This decomposition enables a distinction between risks stemming from direct exposure to climate risks and those resulting from systemic vulnerabilities. To estimate potential systemic losses from extreme climate events (i.e., system-wide climate exposure CoVaR indicator), we aggregate the institution-specific risks weighted by their market capitalization (MV_t^i).

$$VaR_t^{system|VaR_q^f} = \sum_i MV_t^i \, \beta_{q,t}^{(i|f)} VaR_{q,t}^f + \sum_i MV_t^i \, \beta_{q,t}^{(i|\Omega_1')} VaR_{q,t}^{(\Omega_1'|VaR_q^f)} \tag{E.5}$$

The individual C-CoVaR indicator for each financial institution (Equation E.4) is explicitly modeled to account for the direct impact of common climate shocks and the contagion effects propagated through systemic exposure. By capturing these dependencies, we ensure that the resulting individual C-CoVaR reflects institution-specific exposure to systemic climate risk. Consequently, summing these VaR should provide a consistent estimate of the aggregate systemic risk attributable to climate shocks. Nevertheless, we recognize that there may still be residual comovements or other risk channels not fully accounted for in this framework, which could lead to an underestimation of systemic climate risk.

To compute C-CoVaR, we use daily stock returns from 2010–2022 based on the same set of financial institutions as described in Section 2.4. The main specification of our nontail BMG and VMS factors at a daily frequency is f, whereas g is a set of nontail macroeconomic and financial control variables similar to those used in specification (1) in Table A.4. ES is excluded from the control variables because it is only available at a monthly frequency. We run three-year (780 observations) rolling-window quantile regressions for Equation (E.1) as well as for each financial institution (Equation E.2). By setting the parameter q to 0.05, we estimate the daily risk of financial loss due to climate shocks within the system of financial institutions, which should be exceeded once a month.

Figure E.1

Climate exposure CoVaR—transition risk

This figure represents the increase in the 95% daily VaR of the European financial sector associated with a substantial transition-related shock over time (Equation E.5). The left-hand panel shows the conditional VaR of the system as a percentage of its market capitalization, whereas the right-hand panel shows the conditional VaR in billions of euros.

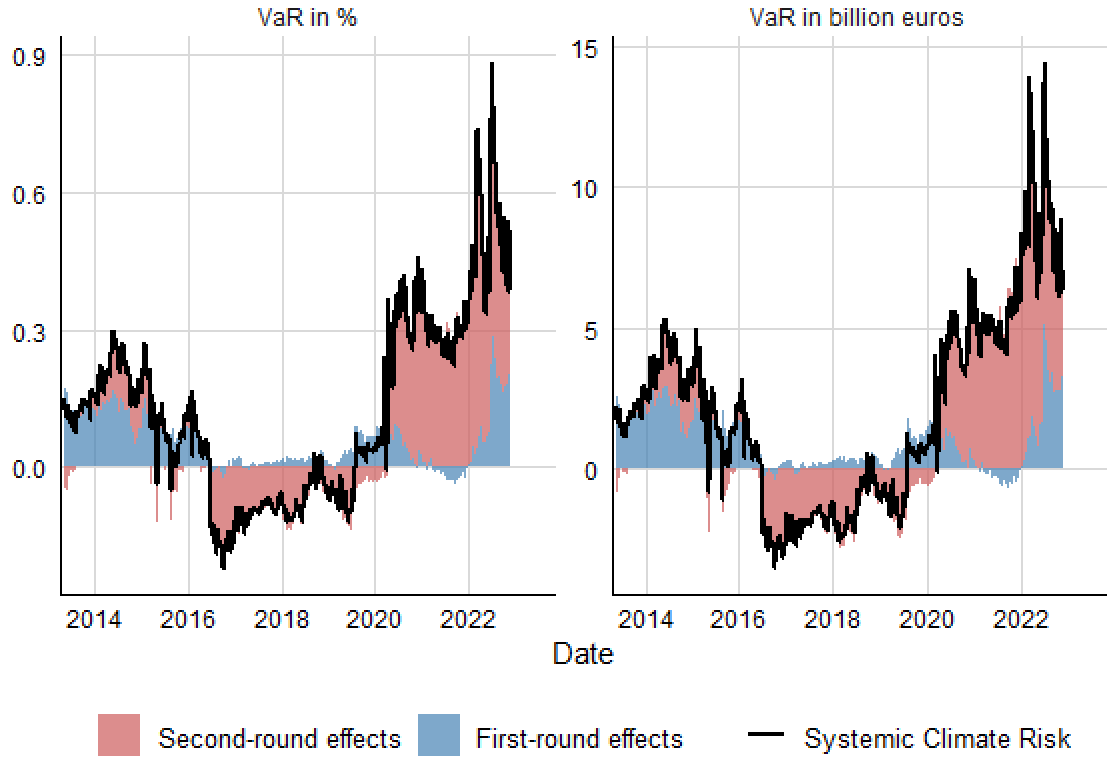
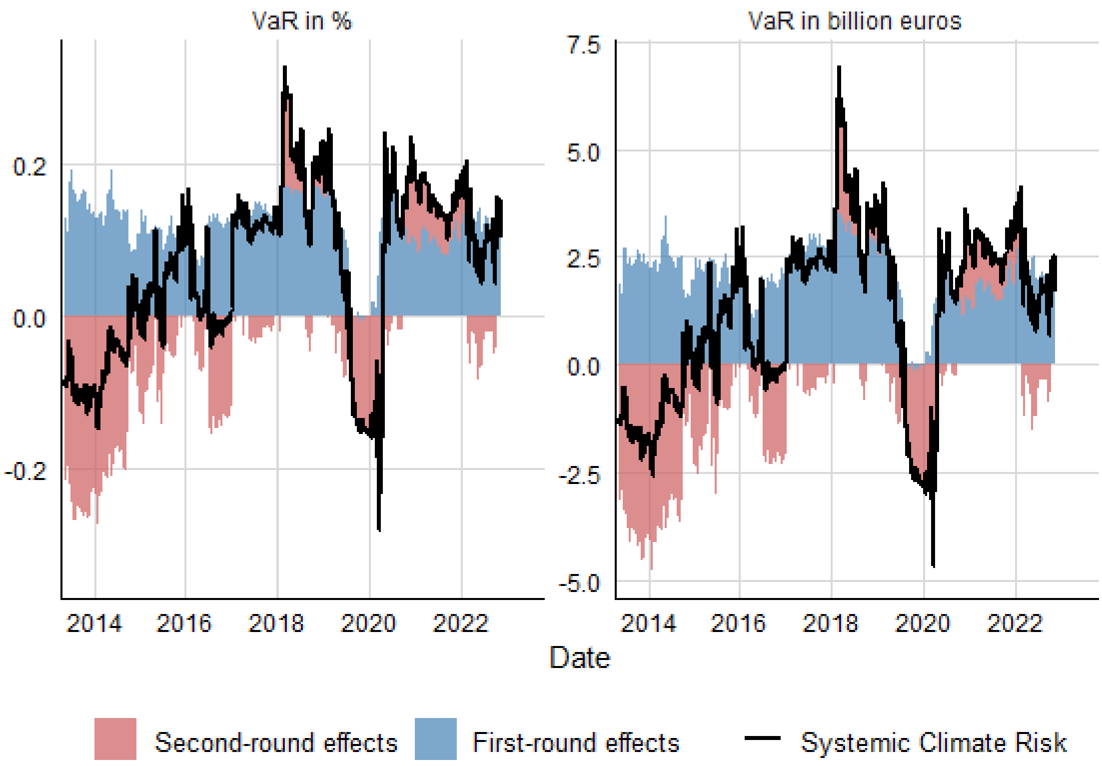


Figure E.2

Climate exposure CoVaR—physical risk

This figure represents the increase in the 95% daily VaR of the European financial sector associated with a substantial physical-related shock over time (Equation E.5). The left-hand panel shows the conditional VaR of the system as a percentage of its market capitalization, whereas the right-hand panel shows the conditional VaR in billions of euros.



Online Appendix

Table OA.1

Most interconnected institutions are based on the VaR and returns.

This table presents a list of the most interconnected institutions based on the VaR and returns by using the loading of each financial institution X_1 on the first principal component Ω_1. The acronyms REIT and REIS stand for "real estate investment trusts" and "real estate investment services", respectively.

Top 30 contributors to Systemic Risk based on VaR measures			Top 30 contributors to Systemic Risk based on stock returns		
Financial institutions	Sectors	X_1	Financial institutions	Sectors	X_1
Erste Group Bank	Banks	8,9%	ING Groep	Banks	8,3%
ING Groep	Banks	8,7%	Societe Generale	Banks	7,9%
Nordea Bank	Banks	8,5%	Erste Group Bank	Banks	7,8%
Societe Generale	Banks	8,5%	Credit Agricole	Banks	7,7%
CRCAM	Banks	8,4%	Nordea Bank	Banks	7,6%
Sparebank 1 SMN Ords	Banks	8,4%	DNB Bank	Banks	7,5%
Bank Polska Kasa Opieki	Banks	8,0%	Banco Santander	Banks	7,5%
Barclays	Banks	8,0%	BNP Paribas	Banks	7,4%
Investec	Banks	8,0%	Unicredit	Banks	7,4%
Intesa Sanpaolo	Banks	8,0%	KBC Ancora	Banks	7,4%
Banco Santander	Banks	7,9%	Barclays	Banks	7,3%
Sparebank 1 Helgeland	Banks	7,9%	Banco Bilbao Vizcaya Argentaria	Banks	7,3%
Vontobel Holding	Banks	7,9%	OTP Bank	Banks	7,3%
PKO Bank	Banks	7,8%	KBC Group	Banks	7,2%
Credit Agricole	Banks	7,8%	Lloyds Banking Group	Banks	7,2%
Banco Bilbao Vizcaya Argentaria	Banks	7,8%	Wendel	Financial Services	8,0%
Jyske Bank	Banks	7,7%	Eurazeo	Financial Services	7,9%
Komercni Banka	Banks	7,7%	GBL New	Financial Services	7,8%
Unicredit	Banks	7,6%	Peugeot Invest	Financial Services	7,5%
Peugeot Invest	Financial Services	8,4%	Intermediate Capital Group	Financial Services	7,4%
Wendel	Financial Services	8,1%	Industrivarden A	Financial Services	7,3%
Eurazeo	Financial Services	8,1%	Legal and General	Life Insurance	7,7%
Intermediate Capital Group	Financial Services	7,8%	Aviva	Life Insurance	7,3%
CNP Assurances	Life Insurance	8,4%	Prudential	Life Insurance	7,3%
Storebrand	Life Insurance	7,8%	Swiss Life Holding	Life Insurance	7,2%
Olav Thon Eiendomsselskap	REIS	7,7%	Sampo 'A'	Nonlife Insurance	7,6%
Nexity	REIS	7,6%	AXA	Nonlife Insurance	7,6%
Eurocommercial Properties	REIT	7,8%	Allianz	Nonlife Insurance	7,5%
Hammerson	REIT	7,8%	Vienna Insurance Group A	Nonlife Insurance	7,4%
Land Securities Group	REIT	7,8%	Helvetia Holding N	Nonlife Insurance	7,3%

Table OA.2

Alternative set of factors—time series dimension

This table presents the determinants of systemic risk based on the time series analysis described in Equation (7). We use Ω_1, the systemic risk measure derived from the first principal component defined in Equation (3), as the dependent variable. The independent variables are the ΔVaR of the risk factors, as described in Section 2.5, except for RR and ES, which are in first differences. Newey–West standard errors are reported in parentheses. ***, **, and * indicate significance at the 1%, 5% and 10% levels, respectively. Standardized regression coefficients are reported. A positive coefficient always indicates that a degradation in the indicator is associated with an increase in systemic risk.

VARIABLES	(1) Ω_1	(2) Ω_1	(3) Ω_1	(4) Ω_1	(5) Ω_1
BMG	0.065*	0.069**	0.096**	0.076**	0.070*
	(0.038)	(0.031)	(0.040)	(0.035)	(0.038)
VMS	0.008	0.028	-0.012	-0.035	-0.011
	(0.028)	(0.041)	(0.035)	(0.040)	(0.031)
MKT	0.307***	0.662***	0.478***	0.468***	0.320***
	(0.089)	(0.083)	(0.069)	(0.067)	(0.078)
ML	0.035				0.010
	(0.053)				(0.029)
DP	0.274***				0.150***
	(0.082)				(0.058)
YC	0.011				0.007
	(0.024)				(0.024)
NS	0.030				0.009
	(0.026)				(0.019)
RR	-0.060*				-0.028
	(0.035)				(0.023)
ES	0.489***				0.333***
	(0.074)				(0.046)
OIL	0.020				0.009
	(0.042)				(0.028)
ME		0.329**	0.061	0.062	0.029
		(0.161)	(0.050)	(0.050)	(0.031)
IA		-0.026	-0.031	-0.025	0.006
		(0.028)	(0.021)	(0.020)	(0.015)
ROE			-0.029	-0.062	-0.047
			(0.069)	(0.064)	(0.058)
EG			0.362***	0.369***	0.134*
			(0.109)	(0.105)	(0.079)
LIQ			0.194***	0.188***	0.112***
			(0.047)	(0.044)	(0.028)
QMJ			0.100	0.096	0.120*
			(0.093)	(0.086)	(0.069)
WML				0.102**	0.083**
				(0.041)	(0.035)
Constant	0.000	-0.001	-0.002	-0.002	-0.006
	(0.025)	(0.033)	(0.027)	(0.026)	(0.019)
Observations	207	203	203	203	203
R-squared	0.864	0.71	0.85	0.858	0.903
Adjusted R-squared	0.857	0.702	0.843	0.851	0.894

Table OA.3

Bootstrapping approach—time series dimension

This table presents the determinants of systemic risk based on the time series analysis described in Equation (7). We use Ω_1, the systemic risk measure derived from the first principal component defined in Equation (3), as the dependent variable. The independent variables are the ΔVaR of the risk factors, as described in Section 2.5, except for RR and ES, which are in first differences. Standard errors are estimated via a bootstrapping approach. Bias-corrected and accelerated 90% confidence intervals are shown in square brackets. Standardized regression coefficients are reported. A positive coefficient always indicates that a degradation in the indicator is associated with an increase in systemic risk. Significant coefficients are indicated in bold text.

VARIABLES	(1) Ω_1	(2) Ω_1	(3) Ω_1	(4) Ω_1	(5) Ω_1
BMG	**0.062** [0.016–0.129]	**0.080** [0.029–0.157]	**0.077** [0.025–0.158]	**0.049** [0.001–0.119]	**0.044** [0.003–0.102]
VMS	0.008 [-0.038–0.078]	-0.001 [-0.053–0.071]	-0.002 [-0.053–0.068]	-0.023 [-0.079–0.043]	-0.017 [-0.064–0.035]
MKT	**0.313** [0.139–0.426]	**0.585** [0.461–0.700]	**0.580** [0.457–0.711]	**0.568** [0.448–0.692]	**0.348** [0.208–0.450]
ML	0.028 [-0.040–0.140]				-0.000 [-0.065–0.076]
DP	**0.275** [0.148–0.441]				**0.169** [0.069–0.309]
YC	0.011 [-0.039–0.063]				0.017 [-0.030–0.073]
NS	0.031 [-0.007–0.108]				0.029 [-0.008–0.105]
RR	**-0.059** [-0.134 – -0.014]				-0.021 [-0.069–0.017]
ES	**0.496** [0.254–0.629]				**0.376** [0.270–0.537]
SMB		**0.227** [0.126–0.413]	**0.223** [0.134–0.432]	**0.223** [0.136–0.421]	**0.109** [0.061–0.209]
HML		**0.377** [0.154–0.548]	**0.385** [0.040–0.577]	**0.370** [0.036–0.562]	**0.130** [0.001–0.278]
RMW			-0.012 [-0.164–0.161]	-0.020 [-0.167–0.146]	0.076 [-0.014–0.176]
CMA			0.019 [-0.046–0.116]	0.017 [-0.047–0.109]	0.007 [-0.045–0.069]
WML				**0.101** [0.044–0.200]	**0.077** [0.030–0.160]
Constant	0.000 [-0.055–0.041]	0.000 [-0.059–0.048]	0.000 [-0.065–0.047]	0.000 [-0.063–0.046]	0.000 [-0.048–0.040]
Observations	207	207	207	207	207
# resampling	9,999	9,999	9,999	9,999	9,999

Table OA.4

Determinants of systemic risk—exponentially decreasing weights

This table presents the determinants of systemic risk based on the time series analysis described in Equation (7). We use Ω_1, the systemic risk measure derived from the first principal component defined in Equation (3), as the dependent variable. We estimate Equation (7) using an exponentially weighted scheme with a decay factor of 0.98, which assigns greater weight to more recent observations. ΔVaR of the risk factors, as described in Section 2.5, except for RR and ES, which are in first differences. Newey–West standard errors are reported in parentheses. ***, **, and * indicate significance at the 1%, 5% and 10% levels, respectively. Standardized regression coefficients are reported. A positive coefficient always indicates that a degradation in the indicator is associated with an increase in systemic risk.

VARIABLES	(1) Ω_1	(2) Ω_1	(3) Ω_1	(4) Ω_1	(5) Ω_1
BMG	0.072*	0.135***	0.175***	0.133***	0.115***
	(0.039)	(0.040)	(0.037)	(0.036)	(0.043)
VMS	0.087*	-0.006	-0.011	-0.015	0.025
	(0.048)	(0.058)	(0.049)	(0.049)	(0.020)
MKT	0.238**	0.648***	0.654***	0.646***	0.355***
	(0.111)	(0.061)	(0.058)	(0.058)	(0.062)
ML	-0.145**				-0.105**
	(0.061)				(0.045)
DP	0.522***				0.265***
	(0.135)				(0.077)
YC	0.001				0.018
	(0.028)				(0.027)
NS	0.062				0.036*
	(0.037)				(0.021)
RR	-0.085				-0.012
	(0.056)				(0.020)
ES	0.406***				0.243***
	(0.062)				(0.053)
SMB		0.347***	0.337***	0.338***	0.179***
		(0.078)	(0.069)	(0.066)	(0.050)
HML		0.394***	0.425***	0.402***	0.229***
		(0.066)	(0.070)	(0.066)	(0.062)
RMW			-0.065*	-0.065**	0.006
			(0.035)	(0.033)	(0.030)
CMA			-0.052*	-0.044*	-0.008
			(0.029)	(0.025)	(0.023)
WML				0.083***	0.056*
				(0.028)	(0.029)
Constant	0.006	-0.012	-0.014	-0.016	-0.004
	(0.044)	(0.041)	(0.035)	(0.035)	(0.028)
Observations	207	207	207	207	207
R-squared	0.913	0.907	0.912	0.915	0.951
Adjusted R-squared	0.909	0.904	0.909	0.912	0.948

Table OA.5

Alternative set of factor loadings—cross-sectional dimension

This table presents the cross-sectional analysis, as described in Equation (9). The dependent variable X_1 represents the loading of each financial institution on Ω_1. The explanatory variables are the coefficients $\hat{\beta}$ extracted from Equation (8). We include industry and country fixed effects and report clustered standard errors at the country level.

VARIABLES	(1) X_1	(2) X_1	(3) X_1	(4) X_1	(5) X_1
$\hat{\beta}_{BMG}$	0.015**	0.022**	0.017**	0.017***	0.011**
	(0.006)	(0.009)	(0.006)	(0.006)	(0.004)
$\hat{\beta}_{VMS}$	-0.009**	-0.009	0.013**	0.009*	0.006
	(0.004)	(0.006)	(0.006)	(0.005)	(0.006)
$\hat{\beta}_{MKT}$	0.014***	0.008**	0.005*	0.007***	0.013***
	(0.003)	(0.004)	(0.003)	(0.002)	(0.002)
$\hat{\beta}_{ML}$	-0.008*				-0.005
	(0.004)				(0.006)
$\hat{\beta}_{DP}$	-0.005**				0.001
	(0.002)				(0.002)
$\hat{\beta}_{YC}$	0.011***				0.010***
	(0.002)				(0.002)
$\hat{\beta}_{NS}$	-0.007				-0.011**
	(0.008)				(0.005)
$\hat{\beta}_{RR}$	-0.022***				-0.028***
	(0.007)				(0.008)
$\hat{\beta}_{ES}$	-0.011*				-0.012**
	(0.006)				(0.006)
$\hat{\beta}_{OIL}$	-0.022***				-0.012*
	(0.004)				(0.006)
$\hat{\beta}_{ME}$		0.013**	0.011**	0.016***	0.018***
		(0.005)	(0.004)	(0.004)	(0.003)
$\hat{\beta}_{IA}$		-0.003	0.011	0.002	-0.006
		(0.010)	(0.011)	(0.010)	(0.012)
$\hat{\beta}_{ROE}$			-0.003	0.025***	0.027***
			(0.004)	(0.005)	(0.003)
$\hat{\beta}_{EG}$			0.010***	0.018***	0.018***
			(0.002)	(0.002)	(0.002)
$\hat{\beta}_{LIQ}$			0.008*	0.004	-0.005
			(0.004)	(0.005)	(0.005)
$\hat{\beta}_{QMJ}$			0.006	0.010***	0.014***
			(0.003)	(0.003)	(0.003)
$\hat{\beta}_{WML}$				0.024***	0.026***
				(0.004)	(0.003)
Observations	371	371	371	371	371
R-squared	0.378	0.313	0.359	0.427	0.508
Adjusted R-squared	0.305	0.243	0.286	0.36	0.438
Country Fixed Effects	Yes	Yes	Yes	Yes	Yes
Industry Fixed Effects	Yes	Yes	Yes	Yes	Yes

Table OA.6

Bootstrapping approach—cross-sectional dimension

This table presents the cross-sectional analysis, as described in Equation (9). The dependent variable X_1 represents the loading of each financial institution on Ω_1. The explanatory variables are the coefficients $\hat{\beta}$ extracted from Equation (8). Standard errors are estimated via a bootstrapping approach. Bias-corrected and accelerated 90% confidence intervals are shown in square brackets. Significant coefficients are indicated in bold text.

VARIABLES	(1) X_1	(2) X_1	(3) X_1	(4) X_1	(5) X_1
$\hat{\beta}_{BMG}$	**0.006** [0.001–0.011]	**0.012** [0.006–0.018]	**0.011** [0.005–0.017]	**0.012** [0.006–0.019]	**0.007** [0.002–0.019]
$\hat{\beta}_{VMS}$	0.001 [-0.001–0.002]	-0.001 [-0.003–0.001]	-0.001 [-0.003–0.001]	-0.000 [-0.002–0.002]	0.001 [-0.006–0.013]
$\hat{\beta}_{MKT}$	**0.030** [0.022–0.036]	**0.013** [0.006–0.021]	**0.009** [0.001–0.016]	**0.011** [0.003–0.018]	**0.026** [0.009–0.017]
$\hat{\beta}_{ML}$	**0.001** [0.000–0.001]				**0.001** [0.000–0.001]
$\hat{\beta}_{DP}$	**0.007** [0.005–0.009]				**0.007** [0.004–0.009]
$\hat{\beta}_{YC}$	-0.004 [-0.007–0.000]				-0.002 [-0.006–0.003]
$\hat{\beta}_{NS}$	-0.002 [-0.003–0.000]				**-0.016** [-0.025 – -0.005]
$\hat{\beta}_{RR}$	-0.002 [-0.006–0.002]				**-0.006** [-0.011 – -0.001]
$\hat{\beta}_{ES}$	**0.062** [0.052–0.074]				**0.053** [0.040–0.067]
$\hat{\beta}_{SMB}$		**0.004** [0.002–0.005]	**0.004** [0.002–0.005]	**0.003** [0.001–0.005]	**0.003** [0.001–0.005]
$\hat{\beta}_{HML}$		**0.004** [0.001–0.007]	**0.007** [0.002–0.010]	**0.005** [0.000–0.008]	**0.007** [0.003–0.010]
$\hat{\beta}_{RMW}$			0.001 [-0.000–0.003]	0.001 [-0.000–0.003]	0.001 [-0.001–0.002]
$\hat{\beta}_{CMA}$			0.001 [-0.005–0.008]	0.004 [-0.002–0.011]	**0.005** [0.001–0.008]
$\hat{\beta}_{WML}$				**0.030** [0.011–0.047]	0.010 [-0.003–0.023]
Constant	**0.015** [0.011–0.019]	**0.026** [0.021–0.030]	**0.025** [0.021–0.031]	**0.023** [0.019–0.029]	**0.013** [0.009–0.018]
Observations	371	371	371	371	371
# resampling	9,999	9,999	9,999	9,999	9,999

Table OA.7

Error-in-Variables—shrinkage

This table presents the cross-sectional analysis, as described in Equation (9). The dependent variable X_1 represents the loading of each financial institution on Ω_1. The explicative variables are the coefficients $\hat{\beta}^{shr}$ extracted from Equation (8) and then adjusted following Equation (13). We include industry and country fixed effects and report clustered standard errors at the country level.

VARIABLES	(1) X_1	(2) X_1	(3) X_1	(4) X_1	(5) X_1
$\hat{\beta}_{BMG}$	0.013* (0.008)	0.026*** (0.009)	0.034*** (0.009)	0.032*** (0.009)	0.020** (0.009)
$\hat{\beta}_{VMS}$	0.002 (0.003)	0.004 (0.005)	0.001 (0.004)	0.004 (0.004)	0.001 (0.003)
$\hat{\beta}_{MKT}$	0.060*** (0.009)	0.064*** (0.015)	0.048*** (0.015)	0.050*** (0.015)	0.050*** (0.008)
$\hat{\beta}_{ML}$	0.0002 (0.000)				0.001*** (0.000)
$\hat{\beta}_{DP}$	0.023*** (0.003)				0.022*** (0.003)
$\hat{\beta}_{YC}$	-0.002 (0.004)				-0.005 (0.006)
$\hat{\beta}_{NS}$	-0.001 (0.003)				-0.008** (0.004)
$\hat{\beta}_{RR}$	-0.023** (0.010)				-0.038*** (0.009)
$\hat{\beta}_{ES}$	0.149*** (0.018)				0.114*** (0.018)
$\hat{\beta}_{SMB}$		0.015*** (0.002)	0.017*** (0.002)	0.015*** (0.002)	0.013*** (0.002)
$\hat{\beta}_{HML}$		0.012* (0.007)	0.019** (0.008)	0.018** (0.007)	0.016** (0.007)
$\hat{\beta}_{RMW}$			0.010*** (0.003)	0.009*** (0.003)	0.005** (0.002)
$\hat{\beta}_{CMA}$			0.029** (0.012)	0.030*** (0.012)	0.029*** (0.008)
$\hat{\beta}_{WML}$				0.057** (0.024)	-0.007 (0.021)
Observations	371	371	371	371	371
R-squared	0.618	0.465	0.493	0.501	0.655
Adjusted R-squared	0.574	0.411	0.439	0.445	0.610
Country Fixed Effects	Yes	Yes	Yes	Yes	Yes
Industry Fixed Effects	Yes	Yes	Yes	Yes	Yes

Table OA.8

Error-in-Variables—IV method

This table presents the cross-sectional analysis, as described in Equation (9). The dependent variable X_1 represents the loading of each financial institution on Ω_1. The explicative variables are computed via the IV method of Jegadeesh et al. (2019). We include industry and country fixed effects and report clustered standard errors at the country level.

VARIABLES	(1) X_1	(2) X_1	(3) X_1	(4) X_1	(5) X_1
$\hat{\beta}_{BMG}$	0.026*	0.051***	0.055***	0.053***	0.023*
	(0.014)	(0.013)	(0.014)	(0.014)	(0.013)
$\hat{\beta}_{VMS}$	-0.002	-0.003	0.001	-0.001	-0.007
	(0.006)	(0.005)	(0.005)	(0.005)	(0.007)
$\hat{\beta}_{MKT}$	0.259***	0.107**	0.118**	0.135**	0.287***
	(0.070)	(0.051)	(0.055)	(0.056)	(0.059)
$\hat{\beta}_{ML}$	0.001				-0.0004
	(0.001)				(0.001)
$\hat{\beta}_{DP}$	0.032***				0.035***
	(0.008)				(0.009)
$\hat{\beta}_{YC}$	0.083				0.278**
	(0.155)				(0.122)
$\hat{\beta}_{NS}$	0.003				0.005
	(0.004)				(0.004)
$\hat{\beta}_{RR}$	0.003				-0.026
	(0.023)				(0.027)
$\hat{\beta}_{ES}$	0.074***				0.077***
	(0.011)				(0.012)
$\hat{\beta}_{SMB}$		0.007***	0.007***	0.006***	-0.001
		(0.002)	(0.003)	(0.002)	(0.004)
$\hat{\beta}_{HML}$		0.067*	0.011	-0.007	-0.015
		(0.034)	(0.039)	(0.044)	(0.047)
$\hat{\beta}_{RMW}$			0.003**	0.003**	-0.001
			(0.002)	(0.002)	(0.002)
$\hat{\beta}_{CMA}$			0.059	0.065	-0.065
			(0.054)	(0.053)	(0.050)
$\hat{\beta}_{WML}$				0.102	0.167***
				(0.066)	(0.052)
Observations	371	371	371	371	371
R-squared	0.355	0.256	0.263	0.267	0.365
Adjusted R-squared	0.281	0.181	0.183	0.185	0.282
Country Fixed Effects	Yes	Yes	Yes	Yes	Yes
Industry Fixed Effects	Yes	Yes	Yes	Yes	Yes

Table OA.9

Determinants of systemic risk—average correlation

This table presents the results of the cross-sectional analysis, as described in Equation (9). The dependent variable is the average correlation of each financial institution's VaR with the remaining system, computed from Σ_{std}. The explicative variables are the coefficients $\hat{\beta}$ extracted from Equation (8). White heteroskedasticity-robust standard errors are reported in parentheses in columns (1) to (4). We include industry and country fixed effects and report clustered standard errors at the country level in columns (5) to (8).

VARIABLES	(1) $Corr_{avg}$	(2) $Corr_{avg}$	(3) $Corr_{avg}$	(4) $Corr_{avg}$	(5) $Corr_{avg}$	(6) $Corr_{avg}$	(7) $Corr_{avg}$	(8) $Corr_{avg}$
$\hat{\beta}_{BMG}$	0.020**	0.043***	0.045***	0.025**	0.022**	0.037**	0.043***	0.030***
	(0.010)	(0.013)	(0.013)	(0.010)	(0.008)	(0.011)	(0.014)	(0.009)
$\hat{\beta}_{VMS}$	0.002	-0.003	-0.0002	0.002	0.003	-0.003	-0.002	0.005
	(0.003)	(0.004)	(0.005)	(0.003)	(0.003)	(0.004)	(0.005)	(0.003)
$\hat{\beta}_{MKT}$	0.111***	0.052***	0.045***	0.098***	0.090***	0.044*	0.037	0.079***
	(0.014)	(0.015)	(0.015)	(0.015)	(0.012)	(0.020)	(0.022)	(0.011)
$\hat{\beta}_{ML}$	0.001**			0.002***	0.001			0.001**
	(0.001)			(0.001)	(0.001)			(0.000)
$\hat{\beta}_{DP}$	0.026***			0.026***	0.028***			0.026***
	(0.004)			(0.005)	(0.004)			(0.005)
$\hat{\beta}_{YC}$	-0.014**			-0.008	-0.01			-0.009
	(0.007)			(0.007)	(0.007)			(0.008)
$\hat{\beta}_{NS}$	-0.007**			-0.012***	-0.008**			-0.014***
	(0.003)			(0.003)	(0.002)			(0.003)
$\hat{\beta}_{RR}$	-0.006			-0.020**	-0.014			-0.031***
	(0.009)			(0.009)	(0.011)			(0.010)
$\hat{\beta}_{ES}$	0.206***			0.176***	0.187***			0.170***
	(0.022)			(0.024)	(0.012)			(0.030)
$\hat{\beta}_{SMB}$		0.012***	0.010***	0.010***		0.011***	0.011***	0.013***
		(0.003)	(0.003)	(0.003)		(0.001)	(0.003)	(0.003)
$\hat{\beta}_{HML}$		0.012**	0.014*	0.020***		0.005	0.009	0.012
		(0.006)	(0.007)	(0.007)		(0.008)	(0.011)	(0.010)
$\hat{\beta}_{RMW}$			0.004	0.002			0.005	0.002
			(0.003)	(0.003)			(0.005)	(0.003)
$\hat{\beta}_{CMA}$			0.016	0.019***			0.016	0.019*
			(0.011)	(0.007)			(0.014)	(0.009)
$\hat{\beta}_{WML}$			0.107***	0.036			0.064*	0.020
			(0.033)	(0.022)			(0.031)	(0.033)
Constant	0.055***	0.094***	0.086***	0.048***				
	(0.009)	(0.009)	(0.009)	(0.009)				
Observations	371	371	371	371	371	371	371	371
R-squared	0.347	0.135	0.167	0.377	0.45	0.296	0.309	0.473
Adjusted R-squared	0.33	0.123	0.149	0.352	0.387	0.225	0.233	0.403
Country Fixed Effects	No	No	No	No	Yes	Yes	Yes	Yes
Industry Fixed Effects	No	No	No	No	Yes	Yes	Yes	Yes

Table OA.10

Tail physical risk and country characteristics—subsample analysis

This table presents a subsample analysis of the associations between country-level climate characteristics and financial institutions' exposure to physical climate risk, $\hat{\beta}_{VMS}$. $\hat{\beta}_{VMS}$ is estimated dynamically on a rolling window of 100 observations from Equation (8). Country-level indicators of physical climate risk are taken from the Notre Dame Global Adaptation Initiative (ND-GAIN). In columns (1) and (2), $Floods$, the projected change in flood hazard, is used. Columns (3) and (4) use $Deaths$, the projected loss of life years. Columns (5) and (6) use $WaterDependency$, the proportion of water resources originating from outside the country. Regressions (1), (3), and (5) use financial institutions with an above-median percentage of international activities (low home bias). Regressions (2), (4), and (6) use financial institutions with a percentage of international activities below or equal to the median (high home bias). The percentage of international activities (activities outside the home country) is obtained from Refinitiv Datastream. All regressions use industry and year fixed effects. Standard errors clustered at the institution level are reported in parentheses. Appendix B presents the variable definitions. ***, **, and * indicate significance at the 1%, 5% and 10% levels, respectively.

VARIABLES	(1) $\hat{\beta}_{VMS_{i,t}}$ Above median international activities	(2) $\hat{\beta}_{VMS_{i,t}}$ Below median international activities	(3) $\hat{\beta}_{VMS_{i,t}}$ Above median international activities	(4) $\hat{\beta}_{VMS_{i,t}}$ Below median international activities	(5) $\hat{\beta}_{VMS_{i,t}}$ Above median international activities	(6) $\hat{\beta}_{VMS_{i,t}}$ Below median international activities
Beta (t-1)	0.633	0.262	0.608	0.170	0.608	0.386
	(0.417)	(0.300)	(0.413)	(0.303)	(0.415)	(0.293)
LogMarketValue (t-1)	-0.121	-0.0917	-0.108	-0.0570	-0.119	-0.102
	(0.0812)	(0.0687)	(0.0828)	(0.0646)	(0.0813)	(0.0690)
Cash (t-1)	-0.0383	-0.274	-0.0725	-0.147	-0.225	-0.393
	(0.822)	(0.625)	(0.780)	(0.587)	(0.817)	(0.642)
NetIncome (t-1)	0.930	-1.102	1.212	-0.302	1.323	-0.833
	(1.294)	(0.704)	(1.237)	(0.684)	(1.269)	(0.735)
MtoB (t-1)	-0.127	0.0685	-0.107	0.0847	-0.101	0.104
	(0.0814)	(0.118)	(0.0805)	(0.105)	(0.0829)	(0.122)
Debt (t-1)	-0.00799	-0.000322	-0.00729	0.000914	-0.00784	-0.000903
	(0.00543)	(0.00353)	(0.00555)	(0.00351)	(0.00555)	(0.00329)
Floods	2.721**	4.043**				
	(1.304)	(1.741)				
Deaths			0.416	1.042**		
			(0.560)	(0.403)		
Waterdependency					0.163	1.514***
					(0.454)	(0.544)
Constant	-1.300	-2.357*	0.448	0.168	0.596	0.364
	(1.133)	(1.359)	(0.637)	(0.348)	(0.660)	(0.317)
Observations	1,593	1,652	1,593	1,652	1,593	1,652
R-squared	0.075	0.054	0.069	0.073	0.068	0.062
Adjusted R-squared	0.063	0.043	0.057	0.061	0.056	0.050
Industry Fixed Effects	Yes	Yes	Yes	Yes	Yes	Yes
Year Fixed Effects	Yes	Yes	Yes	Yes	Yes	Yes

Table OA.11

Pricing of climate risks within nonfinancial firms

This table presents the results of time series regressions of the returns from the 10 portfolios based on climate characteristics on “nontail” climate risk factors (based on 10–1 deciles). Panel A presents the results for portfolios based on GHG emission intensity. Panel B details the results for portfolios based on physical risk scores. Newey–West standard errors are reported in parentheses. ***, **, and * indicate significance at the 1%, 5% and 10% levels, respectively.

Panel A: Portfolios based on GHG emission intensity

	Portfolios based on GHG emission intensity									
	q1	q2	q3	q4	q5	q6	q7	q8	q9	q10
BMG	-0.476***	-0.234***	-0.160*	-0.186**	-0.083	-0.118*	-0.026	0.167**	0.352***	0.474***
	(0.066)	(0.078)	(0.097)	(0.087)	(0.083)	(0.067)	(0.066)	(0.068)	(0.067)	(0.068)
MKT	0.669***	0.624***	0.571***	0.587***	0.558***	0.597***	0.647***	0.670***	0.673***	0.678***
	(0.053)	(0.064)	(0.064)	(0.062)	(0.062)	(0.059)	(0.053)	(0.056)	(0.054)	(0.050)
SMB	0.134	0.221	0.030	0.041	0.003	0.086	0.133	0.088	0.122	0.068
	(0.112)	(0.180)	(0.152)	(0.130)	(0.135)	(0.117)	(0.142)	(0.122)	(0.126)	(0.095)
HML	0.269*	0.314*	0.256	0.378**	0.370**	0.345**	0.147	0.367**	0.309***	0.415***
	(0.148)	(0.185)	(0.195)	(0.168)	(0.174)	(0.144)	(0.153)	(0.162)	(0.117)	(0.136)
RMW	0.444**	0.579*	0.510*	0.575**	0.712***	0.854***	0.506**	0.728***	0.455***	0.380**
	(0.226)	(0.303)	(0.291)	(0.235)	(0.260)	(0.216)	(0.239)	(0.212)	(0.160)	(0.180)
CMA	-0.355**	-0.399**	-0.361*	-0.273	-0.294	-0.152	-0.207	-0.373**	-0.472***	-0.515***
	(0.174)	(0.194)	(0.203)	(0.212)	(0.240)	(0.190)	(0.173)	(0.173)	(0.139)	(0.164)
WML	0.050	-0.039	0.036	0.029	0.016	0.006	-0.075	-0.030	0.021	0.009
	(0.055)	(0.081)	(0.067)	(0.062)	(0.059)	(0.083)	(0.066)	(0.058)	(0.065)	(0.051)
Constant	-0.002	-0.0005	0.001	0.0003	0.0004	-0.002	-0.0003	-0.001	-0.001	-0.001
	(0.002)	(0.003)	(0.003)	(0.002)	(0.002)	(0.002)	(0.002)	(0.002)	(0.002)	(0.002)
Observations	208	208	208	208	208	208	208	208	208	208
R-squared	0.765	0.659	0.626	0.666	0.624	0.649	0.688	0.727	0.769	0.819
Adjusted R-squared	0.757	0.648	0.613	0.654	0.611	0.636	0.677	0.717	0.761	0.813

Panel B: Portfolios based on physical risk scores

	Portfolios based on physical risk scores									
	q1	q2	q3	q4	q5	q6	q7	q8	q9	q10
VMS	-0.812***	-0.143	-0.067	-0.150**	-0.026	-0.125	-0.063	-0.032	-0.128**	0.432**
	(0.119)	(0.115)	(0.077)	(0.075)	(0.069)	(0.092)	(0.081)	(0.112)	(0.062)	(0.203)
MKT	0.655***	0.645***	0.625***	0.705***	0.754***	0.638***	0.613***	0.597***	0.561***	0.620***
	(0.069)	(0.076)	(0.047)	(0.056)	(0.046)	(0.062)	(0.057)	(0.062)	(0.058)	(0.077)
SMB	0.260**	0.813***	-0.144*	0.227*	-0.034	-0.038	-0.292***	-0.187	-0.159	0.178
	(0.127)	(0.144)	(0.086)	(0.125)	(0.100)	(0.163)	(0.110)	(0.115)	(0.112)	(0.143)
HML	0.383**	0.532***	0.185	0.573***	0.477***	0.349	0.002	0.360**	-0.064	0.280
	(0.180)	(0.192)	(0.132)	(0.167)	(0.131)	(0.241)	(0.146)	(0.157)	(0.170)	(0.173)
RMW	0.637***	0.665**	0.410***	0.632***	0.630***	0.871**	0.363	0.886***	0.247	0.463**
	(0.234)	(0.295)	(0.150)	(0.234)	(0.200)	(0.354)	(0.223)	(0.202)	(0.191)	(0.219)
CMA	-0.471**	-0.585**	-0.255	-0.706***	-0.303**	0.009	0.060	-0.164	-0.205	-0.641***
	(0.200)	(0.298)	(0.182)	(0.214)	(0.133)	(0.278)	(0.182)	(0.194)	(0.218)	(0.197)
WML	-0.013	-0.005	0.126***	0.028	0.011	-0.048	-0.014	0.004	-0.021	0.029
	(0.051)	(0.066)	(0.042)	(0.053)	(0.055)	(0.076)	(0.065)	(0.048)	(0.070)	(0.055)
Constant	-0.003	-0.004	0.0003	-0.003	-0.003	-0.001	0.001	-0.001	0.002	0.0004
	(0.002)	(0.003)	(0.002)	(0.002)	(0.002)	(0.003)	(0.002)	(0.002)	(0.002)	(0.002)
Observations	208	208	208	208	208	208	208	208	208	208
R-squared	0.760	0.677	0.676	0.744	0.781	0.654	0.675	0.650	0.603	0.611
Adjusted R-squared	0.751	0.665	0.665	0.735	0.773	0.642	0.663	0.638	0.589	0.597

Table OA.12

Placebo test (1990–2005)

This table presents the determinants of systemic risk based on the time series analysis described in Equation (7) from 1990–2005. We use Ω_1, the systemic risk measure derived from the first principal component defined in Equation (3), as the dependent variable. The independent variables are the ΔVaR of the risk factors, as described in Section 2.5. ES is in first difference. For reasons of data availability, we adapt certain control variables. ML, DP, and YC are constructed from US data. NS is based on the difference between the average rates of Ireland, Spain, and Italy compared with Germany. RR is not available for the analysis period and has therefore been suppressed. Newey–West standard errors are reported in parentheses. ***, **, and * indicate significance at the 1%, 5% and 10% levels, respectively. Standardized regression coefficients are reported. A positive coefficient always indicates that a degradation in the indicator is associated with an increase in systemic risk.

VARIABLES	(1) Ω_1	(2) Ω_1	(3) Ω_1	(4) Ω_1	(5) Ω_1
BMG	-0.125**	-0.079	-0.078	-0.091	-0.123**
	(0.058)	(0.070)	(0.076)	(0.080)	(0.054)
VMS	0.081	0.139	0.094*	0.05	0.001
	(0.060)	(0.096)	(0.057)	(0.048)	(0.036)
MKT	0.499***	0.693***	0.663***	0.644***	0.469***
	(0.079)	(0.139)	(0.131)	(0.138)	(0.087)
ML	0.028				0.037
	(0.030)				(0.026)
DP	0.431***				0.426***
	(0.098)				(0.093)
YC	0.134**				0.113**
	(0.061)				(0.044)
NS	0.058				0.062
	(0.065)				(0.050)
ES	0.014				0.029
	(0.053)				(0.053)
SMB		-0.125	-0.126	-0.114	-0.151**
		(0.081)	(0.079)	(0.083)	(0.065)
HML		0.042	0.031	-0.025	-0.028
		(0.039)	(0.056)	(0.071)	(0.050)
RMW			0.124	0.085	0.091**
			(0.077)	(0.069)	(0.036)
CMA			-0.03	-0.051	-0.016
			(0.064)	(0.057)	(0.052)
WML				0.194**	0.127**
				(0.088)	(0.059)
Constant	0	0	0	0	0
	(0.046)	(0.058)	(0.060)	(0.063)	(0.042)
Observations	169	169	169	169	169
R-squared	0.669	0.526	0.537	0.561	0.715
Adjusted R-squared	0.653	0.511	0.517	0.539	0.691