Systemic Climate Risk

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Abstract

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JEL Classification: G10, G20, G32, Q54

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

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Abstract

This paper proposes a market-based framework to study systemic climate risks in the financial sector. Our framework aims to identify the financial institutions most vulnerable to physical and transition climate risks and proposes a test to estimate whether climate risks can generate contagion effects in the financial sector. We apply our framework to large European financial institutions and show that, unlike physical risk, transition risk significantly influences systemic risk. We also show that the exposure to transition risk appears lower for institutions with cleaner investment and lending portfolios and long-term orientation.

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1. Introduction

In 2015, the governor of the Bank of England stated that climate change can profoundly affect asset prices and financial stability (Carney, 2015). Since then, the potential systemic impact of climate risks has become a central concern in the financial community (Stroebel and Wurgler, 2021). Climate risks are generally decomposed into physical risks, stemming from the effects of climate change and climate-related hazards (e.g., heat waves, extreme precipitation, wildfires, etc.), and transition risks, arising from changes in the preferences of stakeholders, changes in regulation, legal exposure due to contributing to climate change, and climate-related technological disruption (Krueger et al., 2020, Stroebel and Wurgler, 2021). Physical and transition risks can adversely affect financial institutions through, for example, losses in the value of financial portfolios, increases in claims paid by insurers, or decreases in the creditworthiness of borrowers. These shocks can pose a threat to financial stability if they occur simultaneously or if an extreme shock is transmitted to other institutions through the network of financial interconnections. We refer to these threats to the financial system emanating from climate risks as "systemic climate risks."

This article proposes a new empirical framework based on environmental and stock market data to assess whether climate risks influence systemic risk within the financial sector. From a theoretical perspective, the economic rationale for using a market-based approach to assess the effect of climate risks on systemic risk is that climate risks should lead to a repricing of securities held by financial institutions. Our framework provides a tool to identify *which* financial institutions are the most vulnerable to climate risks and explore *how* financial institutions and policymakers might undertake actions to reduce systemic climate risk. While recent studies focus on individual vulnerabilities (e.g., Alessi et al., 2021; Jung et al., 2021;

Ojea-Ferreiro et al., 2022), our framework proposes a test procedure to assess whether climate risks can exacerbate contagion effects among financial institutions, which is a key element to assess the level of systemic risk in the financial sector (e.g., Billio et al., 2012). Therefore, our approach has the advantage of taking into account potential second-round effects of climate risks within the financial sector, these effects being generally overlooked but representing an important source of systemic risk (Duarte and Eisenbach, 2021).[1] Indeed, common holdings of different market participants, direct interdependencies among financial institutions, and potential fire-sale dynamics could amplify the impact of climate risks on financial stability. Additionally, our framework allows us to estimate the effect of both transition and physical risks on different types of financial institutions, namely banks, insurers, financial services companies, and real estate investment firms. To our knowledge, this paper is the first to provide a broad measure of systemic climate risk based on market data, which captures first- and second-round effects of climate risks on the entire financial sector.

We proceed in several steps. *First*, for the purpose of 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). Our approach can estimate covariations in tail risk across a large number of financial institutions. More specifically, we estimate time-varying Value-at-Risk (VaR) from the stock returns of financial institutions using a GARCH model. Equity returns are meant to be informative about the risks of financial institutions and to reflect information more quickly than accounting variables.[2] Furthermore, the use of tail risk measures meets our objective of analyzing whether climate risks threaten financial stability. Based on principal component analysis, we extract the first principal component from the correlation

[1] See also here.
[2] We use equity data instead of CDS data for consistency with the next steps in the framework.

matrix among the time variations in individual VaR measures. The first principal component provides a dynamic indicator of systemic risk that captures common shifts in financial institution tails, i.e., tail risk dependence within the financial sector. The loadings of each institution on the first principal component represent their respective contribution to global downside risk.

Second, we construct climate risk factors that disentangle between transition and physical risks. Using a large sample of dead and active stocks issued by non-financial companies, we build two long-short factor mimicking portfolios, respectively based on carbon emission intensities and physical risk scores. These factors aim to capture the effect of climate shocks on the value of non-financial firms, to which financial institutions are exposed through loans, portfolio holdings, or insurance contracts. These factors are then used in a regression scheme (detailed below) to analyze the sensitivity of financial institutions to climate shocks through their exposures to non-financial firms. Since we are interested in extreme climate risks and for consistency with the first step, we estimate the VaR of each climate risk factor based on the aforementioned approach. To our knowledge, few papers analyze both physical and transition risks, and this article is the first to focus on extreme climate risks in this context.

Third, we propose a two-pass procedure to assess whether climate risks can exacerbate tail risk dependence among financial institutions. We build on the protocol suggested by Pukthuangthong et al. (2019) to evaluate whether risk factors are related to stock return comovements and extend their approach to tail risks. An initial test, based on a time-series regression, aims to verify whether a rise in climate risks is associated with a simultaneous increase in downside risk within the financial sector. In addition, we propose a complementary test that exploits cross-sectional information on individual climate risk exposures and individual contributions to systemic risk. The objective is to examine whether the institutions most exposed to climate risks contribute more to global downside risk. Financial institutions' exposures to climate risks are derived from the sensitivity of the time variations in the VaR of each financial institution to climate risk factors. This individual measure is an extension of Adrian and Brunnermeier's (2016) work, akin to a “Climate” Exposure CoVaR[3] measure, that incorporates extreme climate risks as potential stress factors for financial institutions.

Fourth, we investigate the characteristics of the financial institutions that correlate with individual climate risk exposures. Specifically, we examine the relationship between individual levels of climate risk exposure and various financial characteristics, institutional ownership, as well as environmental and governance features. We notably include indirect carbon emissions originating from the holding of securities and loans by financial institutions in our list of regressors. Then, we study how various initiatives, and notably the disclosure of environmental information, interact with our market-based measure of climate risk. In short, this fourth step assesses whether the pricing of financial institutions’ exposure to climate risks incorporates extra-financial information, and how financial institutions react to their climate risk exposure. Understanding the factors affecting individual climate risk exposure is essential for regulators and financial practitioners to undertake actions to mitigate systemic climate risks.

Overall, our framework provides a flexible tool to assess the current level of vulnerability of financial institutions to climate risks. 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 dynamically monitor whether the effect of climate risks on financial stability is becoming a growing concern from an investor perspective. Our approach can also help financial institutions and supervisors identify levers to mitigate systemic climate risks. While an

[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.

alternative approach is to examine financial institutions' holdings of brown companies (e.g., Battiston et al., 2017; ECB-ESRB, 2021), our framework provides insight into whether systemic climate risks are reflected into asset prices and whether climate shocks are already propagating to financial institutions. In addition, our climate risk estimates can take into account factors of resilience and vulnerability within the financial sector, as investors are likely to respond more acutely to climate shocks when financial institutions' balance sheets are impaired. Finally, we believe that, based on historical findings, our framework can help estimate the potential loss in the market value of financial or non-financial industries due to future climate shocks. Therefore, our approach should also be considered complementary to research on the development of climate scenarios and assumptions about the future impact of climate risks on the financial system (e.g., Dietz et al., 2016; Battiston et al., 2017; Roncoroni et al., 2021; Vermeulen et al., 2018; Alogoskoufis et al., 2021), which are subject to uncertainty (Barnett et al., 2020).

We apply our framework to a sample of European financial stocks, spanning from 2005 to 2022 and extracted 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 (see Amel-Zadeh and Serafeim, 2018).[4] Second, an increase in systemic risk could lead to more severe economic consequences in Europe, as the failure of European institutions would typically be of large magnitude when compared to the domestic GDP (Engle et al., 2015). Third, it allows us to leverage our access to confidential regulatory

[4] 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 in the US over the period 2014-2020.

data from the Eurosystem on institutional holdings. For financial institutions, we focus on 371 stocks with a market capitalization above €100 million on average over the entire period.

Our results indicate that transition risks significantly affect the VaR of European financial institutions, particularly in the case of life insurance companies and real estate investment trusts. More importantly, we show that transition risks can exacerbate tail risk dependence within the European financial sector, even if the magnitude of the effect appears moderate. As far as we know, this finding constitutes the first empirical evidence of potential contagion effects within the financial sector originating from climate shocks, whether from common risk exposures, spillovers, or pure contagion (Masson, 1998). By contrast, we do not find evidence of such contagion effects in the case of physical climate risks. This result is in line with recent surveys (Krueger et al., 2020; Stroebel and Wurgler, 2021) indicating that financial researchers and practitioners consider that the materialization of regulatory risk is more immediate than that of physical risks. Moreover, the disagreement between physical risk scores of different data providers may create dispersion in investment flows in the event of a natural disaster, limiting or delaying the incorporation of physical risks into asset prices (e.g., Billio et al., 2021 for ESG scores; see Section 2.2). 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, mainly for banks and insurance companies, reaching a peak in 2021.

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 and incentivize board members to consider the longer term. Using Scope 3 carbon data emissions, we also show that institutions with cleaner investment and lending portfolios tend to be less exposed to transition risks. This result is interesting in two respects. First, it tends to validate that our individual Climate Exposure CoVaR measure captures the exposure of financial institutions to transition risk through the investment channel. Second, it suggests that our Climate Exposure CoVaR measure could help compensate for the limited availability of Scope 3 carbon emission data. Besides, we proxy long-term orientation by institutional ownership and long-term incentives to board members, and find a negative relationship between long-term orientation and transition risk exposure. Finally, our results indicate that financial institutions with higher exposure to climate risk tend to selectively disclose extra-financial information, which raises suspicion of greenwashing under the definition proposed by Yu et al. (2020). We also find that financial institutions react to physical risks by engaging in initiatives aiming to improve their environmental footprint.

Our study is linked to the literature on the integration of climate risks into financial market prices. Many papers find 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 (e.g., Bernstein et al., 2019; Baldauf et al., 2020; Murfin and Spiegel, 2020) or bond markets (e.g., Ferriani, 2022; Flammer, 2021; Zerbib, 2019). Despite these premiums, other papers point out 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., 2021).[5] We contribute to this literature by proposing a flexible framework to assess whether extreme climate risks are reflected in the tail risk of equity markets. While this study focuses on the European financial sector, we believe that the proposed framework can be easily adapted to other countries, industries, and asset types.

[5] All these articles should be conceptually distinguished from studies assessing how considerations on Corporate Social Responsibility (CSR) affect asset returns, for example, Pástor et al. (2021), and Pedersen et al. (2021). CSR is defined by Liang and Renneboog (2020) as the internalization by firms of the externalities they create.

Another strand of literature focuses on the effect of environmental risks on financial stability. Lins et al. (2017) show that firms with good ESG (Environmental, Social, Governance) scores performed better during the global financial crisis, while Ilhan et al. (2021b) find that brown stocks are more exposed to tail downside risks based on options market prices. Several articles examine 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), or equity mutual funds (Cerqueti et al., 2021). In a contemporary study, Jung et al. (2021) develop an individual climate systemic risk measure (CRISK), derived from the SRISK indicator (Brownlees and Engle, 2017), which focuses on banks' exposure to fossil fuels. Related methodologies to assess climate risk exposures of financial institutions have also been proposed by Alessi et al. (2021) and Ojea-Ferreiro et al. (2022). Our contributions to this literature are threefold. First, our study includes all types of financial institutions and focuses on both transition and physical extreme climate risks. Second, we propose a novel individual climate risk measure for financial institutions, the Climate Exposure CoVaR, derived from Adrian and Brunnermeier's (2016) work. Third and most importantly, we design a test procedure to analyze whether climate risks affect the overall level of systemic risk in the financial sector. Therefore, our framework captures potential contagion effects across financial institutions, a key aspect of systemic risk, allowing us to account for potential second-round effects of climate risks.

Finally, our study contributes to the literature on the determinants and reactions to climate risks. Several papers examine 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). Besides, using earnings call transcripts, Li et al. (2020) and Sautner et al. (2020) build firm-level measures of climate risk and investigate which characteristics correlate with these measures as well as how firms respond to these risks. Our paper takes a different approach that analyzes climate risk exposures at the corporate level from the perspective of investors. To the best of our knowledge, we are the first to study a large range of potential characteristics associated with a climate risk measure derived from market data, including environmental and governance features, Scope 3 carbon emissions, and information on institutional ownership. Finally, we complement the literature on the determinants of voluntary nonfinancial disclosure (e.g., Dhaliwal et al., 2011, Ilhan et al., 2021a, Reid and Toffel, 2009), by testing whether the financial institutions with high exposure to climate risks tend to disclose more information about these risks.

The rest of the paper is as follows. We present the data and methodology in Section 2, the empirical results in Section 3, and we conclude in Section 4.

2. Data and methodology

2.1. Systemic risk measure

We define a measure of systemic risk among financial institutions based on common variations in the VaR of financial institutions. Our measure captures two important elements of systemic risk: individual tail risks and interdependences. Our systemic risk measure shares similarities with previous studies, namely Adams et al. (2014), Adrian et al. (2016), and Kelly and Jiang (2014). Nevertheless, the proposed indicator presents certain discrepancies with the existing literature, both in terms of target and methodology, making it more suitable for the needs of our study. While the CoVaR indicator of Adrian et al. (2016) examines how each institution contributes to the financial sector's tail risk, which can raise reverse causality issues, we directly estimate simultaneous VaR changes across all financial institutions. This approach allows us to put more emphasis on the overall level of tail risk dependence, leaving aside the question of the directionality of spillovers. Our setup also shares similarities with Adams et al. (2014), as we first estimate the VaR (see Appendix A) of each financial institution and then investigate their comovements. The main originality of our approach compared to theirs lies in extracting common variations in VaR based on a principal component analysis. 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 a large number of financial institutions.[6] Finally, our method is linked to that of Kelly and Jiang (2014) who directly estimate common dynamics in the tail risk of firms using the cross-section of returns. An attractive feature of our measure compared to Kelly and Jiang's (2014) approach is the ability to derive time-varying individual measures of tail risk.

The principal component analysis is based on a singular value decomposition of the correlation matrix:

$$\Xi = [diag(\sum)]^{-1/2} \sum [diag(\sum)]^{-1/2} \qquad (1)$$

with $\sum$ the covariance matrix between the time variations in the VaR of financial institutions. The estimation of the VaR is described in Appendix A. We focus on a 1-month 95%-VaR that represents the negative return that will not be exceeded within this month with a 95 % probability. In our framework, we take the VaR in first difference (ΔVaR) to ensure stationarity, such as $\sum = N^{-1}T^{-1}\overline{\Delta VaR}'\overline{\Delta VaR}$, N being the number of financial institutions, T the length of the period, and $\overline{\Delta VaR}$ a matrix of de-meaned ΔVaR. We perform the principal component analysis on the correlation matrix rather than the covariance matrix because using the

[6] Note that 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.

covariance could lead to an overrepresentation of relatively small institutions with high variance. We can define the estimator of systemic risk and its loadings from Equations (2) and (3):

$$\widehat{\Omega} = T^{1/2}\, \xi' \tag{2}$$

$$\hat{X} = T^{-1}\overline{\Delta VaR}\, \widehat{\Omega}' \tag{3}$$

where $\xi\colon [\xi_1, \dots, \xi_j]$ are the normalized eigenvectors corresponding to the largest eigenvalues of Ξ. Our time series estimator of systemic risk is given by $\widehat{\Omega}_1$, the first principal component extracted from the correlation matrix Ξ. The loadings of each financial institution to $\widehat{\Omega}_1$ are given by $\hat{X}_1$, a $N \times 1$ vector extracted from the $\hat{X}$ matrix.

We apply this approach to the entire sample of financial institutions from 2005 to 2022. The first principal component explains 27.9% of the variance of the database, compared to 6.5% for the second, which is satisfactory considering the dimensionality of the database. Note that the main results in the rest of the paper are also robust to the use of Sparse PCA, which helps to handle the high cross-sectional dimensionality of the data by introducing sparsity structures to the input variables. While 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 (see Section 3.1).

Figure 1 represents the time-varying systemic risk indicator ($\widehat{\Omega}_1$) for all institutions from February 2005 to April 2022, estimated from the PCA analysis. $\widehat{\Omega}_1$ captures common variations in financial institutions' tail risk. 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 the European Covid-19 outbreak in March 2020. Compared to the global financial crisis in 2008, the Covid-19 shock led to a more sudden increase in market volatility, which explains that the extremum is reached during the Covid-19 outbreak.

Besides, Table 1 shows the biggest 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. While real estate companies are absent from the sample based on returns, five real estate institutions appear in the ranking based on tail risks. In addition, whereas 9 insurance companies are gathered in the sample based on returns, only 2 emerge when tail risks are 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 from newspapers. Choi et al. (2020) rely on Google trends. Briere and Ramelli (2021) construct a climate stress indicator using investor flows toward sustainable exchange-traded funds. Finally, some articles explore investors' attention to climate risks by building long-short portfolios based on market and environmental variables (e.g., Görgen et al., 2020; Hsu, et al., 2022).We follow this last approach, as it directly captures the effect of climate characteristics on the returns of non-financial stocks.

2.2.1. Factor construction

We construct two climate risk factors using a large sample of dead and active European stocks (excluding financial sector companies). The factors are based on long-short mimicking portfolios following the standard approach in the asset pricing literature (e.g., Fama and French, 1993, 2015). Each month, we sort non-financial stocks into 5 quintile portfolios based on climate characteristics and then calculate the return spread between the 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. We thus ensure that no portfolio ever contains fewer than 80 stocks, with an average of 200 stocks by 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). Finally, since we are interested in extreme climate risks and for consistency with the first step, we estimate the VaR of each climate risk factor based on a GARCH model, as described in Appendix A.

In the case of transition risks, the long and short positions are determined by their carbon emission intensity.[7] We use both reported and estimated emissions, Scopes 1 & 2, divided by net sales, from Refinitiv Datastream. We do not include Scope 3 because policy authorities and consumers might consider it beyond the scope of the company alone to reduce this emission scope. To mitigate correlation with existing factors (see Table 2), the transition risk factor is

[7] As pointed out by Giglio et al. (2021), measuring transition risk using carbon emissions is the most common approach, even if other possibilities exist. We choose to use carbon emissions because it is a "fundamental" measure of transition risk (as opposed to firm-level scores capturing transition risk via an aggregation of different data sources on "fundamentals"). While carbon emissions are likely to capture risks arising from changes in regulation and consumer preferences, they might fail to reflect the risks of climate-related technological disruption.

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 carbon emissions (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 the market capitalization and the book-to-market at date *t*-1 in our sample.

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

where BMG, which stands for "Brown-minus-Green", represents the returns of the transition risk factor, LB, HB, SB, 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 carbon emission data are updated at a yearly frequency, the portfolios are rebalanced monthly according to the previous month's value of the respective characteristics. At a given period, we include in the portfolios only those non-financial stocks for which data for all characteristics are available. In 2005, data were available for about 400 European non-financial stocks, compared to 2,070 in 2022. Our study starts in 2005 because there is not enough data available on CO2 emissions before this date.

In the case of physical risks, 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, wildfire). Specifically, we use the Composite Moderate 2050 score, representing the physical risk exposure at the horizon of 2050 if climate change is moderate (Representative Concentration Pathway 4.5).[8] In contrast with BMG, the correlation between the physical climate risk factor and the "value" factor (HML) is naturally low (see Table 2), so

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

we only filter portfolios 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"):

$$VMS_t = \frac{SV_t + BV_t}{2} - \frac{SS_t + BS_t}{2} \tag{5}$$

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 for BMG, the allocation of VMS is rebalanced on a monthly basis, but the physical scores are fixed over time.

2.2.2. Factor analysis

The cumulative returns of our climate risk factors are plotted in Figure 2. We observe that the transition and physical risk factors have underperformed over time, which could be due to the occurrence of unexpected climate shocks that are expected to affect brown assets negatively (Pedersen et al., 2021). The trend is more pronounced for the transition risk factor.

Then, we examine how our transition and physical risk factors react to exogenous climate shocks, as well as climate news that tend to reflect climate-related policy events. For exogenous climate shocks, we use the monthly abnormal temperatures in Europe from the National Centers for Environmental Information and the monthly damages associated with climate-related natural disasters in Europe from the International Disaster database (EM-DAT). For European climate news, we rely on the monthly indicator produced by the Cooperative Institute for Research in Environmental Sciences of the University of Colorado. Since we consider that climate news can affect people's attention over the medium term, we smooth the time series by setting the value of the indicator at each month as an exponentially decreasing weighted average over the last twelve months. In Table 3, we calculate the average returns of our climate factors conditional on the value of the climate shock and climate news indicators. We show that the transition risk factor responds negatively to high abnormal temperatures, indicating that carbon-intensive firms tend to underperform low-carbon firms in hot weather. Similarly, we find that the transition risk factor reacts negatively when media attention on climate-related issues is high. With respect to the physical risk factor, our results also indicate that the returns of the most vulnerable firms tend to underperform those of the safest firms in the event of a natural disaster. Overall, these findings highlight that our climate risk factors capture a wide range of climate-related shocks that affect the value of non-financial companies.

Table 4 reports 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 a high sectoral concentration in both the long and short portfolio allocations. For example, firms from the personal goods and software industries, two low-carbon sectors, are most represented in the green portfolio, while companies from the oil and gas production industry, a very carbon-intensive sector, are most often found in the brown portfolio. We also note that the divergence in firm size between the green and brown portfolios is relatively small compared to the difference in carbon intensity. The weighted average market capitalization amounts to €6,331 million for the green portfolio, against €6,866 million for the brown portfolio, while the weighted average carbon intensity is equal to 0.28 % and 934 %, respectively.

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 weighted average market capitalization amounts to €5,723 million for the vulnerable portfolio, against €1,123 million for the safe portfolio. The vulnerable and safe portfolios have an average physical risk score of 62.4 and 32.0, respectively.[9] To alleviate the effect of the size divergences, we control for market capitalization in the construction of the BMG and VMS factors (see Equations 4- and 5).

2.2.3. Factor robustness

We recognize that our main conclusions in the rest of the article may depend on the specification of our climate risk factors. To alleviate this concern, we test the robustness of our key results based on alternative climate risk factors. For the transition risk factor, instead of using the reported and estimated Scope 1 and 2 emissions from Refinitiv Datastream, we construct an alternative version based on reported Scope 1 emissions only. The correlation between the two alternative factors is equal to 90% and the main results are unchanged whether we use the first or the second.

Regarding the physical risk, as an alternative to using Trucost's physical risk score, we construct two factors based on the physical risk scores from Carbone4Finance and ISS-ESG[10], respectively. The average correlation between the three factors is relatively low (27%), highlighting the existence of significant disagreement on the exposure of non-financial firms to physical risk. The difference in firm coverage across data providers could also mechanically reduce the correlation between the factors. However, our main results are robust to the different physical risk factor specifications (see Section 3.2). In all cases, we find no evidence that physical risks have significant effects on systemic risk within the financial sector. Besides the

[9] 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).
[10] The physical score of ISS-ESG represents the fraction of each issuer value susceptible of being lost due to physical climate risks by 2050 in a likely climate-change scenario.

fact that investors appear to view physical risk as a long-term risk (Stroebel and Wurgler, 2021), the lack of results could 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 risks into asset prices. This effect is examined by Billio et al. (2021) for ESG scores.

2.2.4. Factor VaR

Our measure of systemic risk is derived from the VaR of 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 the Appendix. The transformed factors, named $\Delta\widehat{VaR}_{BMG}$ and $\Delta\widehat{VaR}_{VMS}$, reflect the dynamics of tail climate risks. They represent the estimated loss of a long-short portfolio that, within a given month, will not be exceeded with a certain probability. An increase in tail climate risks may result from a higher risk of correction in carbon-intensive stocks or an increase in the probability of outperformance in low carbon stocks, which is likely to occur in the event of unexpected 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 feature 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).

2.3. Climate Exposure CoVaR indicator

We assume a reduced-form factor structure for the variations in the estimated VaR of financial institutions, such as $\Delta\widehat{VaR}_\iota$ satisfies the following linear factor model:

$$\Delta\widehat{VaR}_{i,t} = \alpha_i + \beta_{i,f} f_t + \beta_{i,g} g_t + \varepsilon_t \tag{6}$$

where $\Delta\widehat{VaR}_{i,t}$ represents the estimated variations in extreme risk for each financial institution i in period t (see Appendix), f is a set of climate risk factors that we proxy with $\Delta\widehat{VaR}_{BMG,t}$ and $\Delta\widehat{VaR}_{VMS,t}$, the tail transition and physical climate risk factors, constructed in Section 2.2. The factor set g contains control variables that can help explain the level of systemic risk in the European financial sector. Since our systemic risk measure is derived from equity market data, we first incorporate a selection of systematic risk factors that help explain risk and returns in the equity market (see Harvey et al, 2016). Their inclusion seems particularly relevant in the context of systemic risk, as these factors are supposed to reflect "different set of bad times" (Ang, 2014). For consistency with the dependent variable, we estimate the VaR of these systematic risk factors, which seems well suited to capture the "bad times" in question. Our full selection of systematic risk factors is described in Section 2.4. In addition, we include more comprehensive macroeconomic and financial variables that reflect the degree of risk aversion in the euro area, the liquidity of the interbank market, the default premium, and the state of economic activity (see Section 2.4 for more details). Finally, note that the error term ε_t is subject to $\mathrm{E}[\varepsilon_t|\mathrm{F}_{t-1}] = 0$ and $\mathrm{Cov}\left[\varepsilon_t, f_{i,t}\middle|\mathrm{F}_{t-1}\right] = 0$, where F_{t-1} is the lagged information set.

The coefficient $\beta_{i,f}$ is akin to a "Climate" Exposure CoVaR indicator, as it analyzes how tail climate risks contribute to each financial institution's stress. We estimate Equation (6) using the Mean-Group (MG) estimator of Pesaran, (1995). We run separate regressions for each financial institution, first over the entire period from 2005 to 2022, and then dynamically based on a rolling window of 100 monthly observations. This step allows us to estimate the sensitivity of the VaR of each institution to tail climate risks, i.e., the "Climate" Exposure CoVaR indicator. Next, we aggregate individual coefficients and compute standard errors. Following Pesaran (1995), the MG estimates and their asymptotic variance are consistently estimated by:

$$\hat{\beta}_{MG,t} = \frac{1}{N}\sum_{i=1}^{N}\hat{\beta}_{i,t} \tag{7}$$

$$\hat{\sigma}^2_{\hat{\beta}_{MG,t}} = \frac{1}{N(N-1)}\sum_{i=1}^{N}(\hat{\beta}_{i,t} - \hat{\beta}_{MG,t})(\hat{\beta}_{i,t} - \hat{\beta}_{MG,t})' \tag{8}$$

with $\hat{\beta}_{i,t}$ the exposure of financial institution *i* to either transition or physical risk at time *t*. The subscript *t* should be ignored for static coefficients. To mitigate the risk that errors in individual estimates from Equation (6) bias the MG estimates in Equations (7) and (8), we compute the mean using a robust regression of individual estimates on a single cross-section 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 types, and compute the respective confidence intervals.

2.4. Two-pass test procedure

In this section, we propose a two-pass regression procedure to test whether climate risks can generate contagion among financial institutions. We adopt a general definition of contagion that encompasses common risk exposures, spillover or pure contagion (Masson, 1998). Our test procedure builds on the protocol suggested by Pukthuangthong et al. (2019) to evaluate whether risk factors are related to stock return comovements. We extend their approach to tail risks and propose a complementary test that exploits the cross-sectional dimension. From Equation (9), the covariance across $\Delta\widehat{VaR}_i$, noted $\sum$, is determined by the following relation (after suppressing time subscripts):

$$\sum = \beta_f \beta_f' var(f) + \beta_g \beta_g' var(g) + (\beta_g \beta_f' + \beta_f \beta_g') cov(f,g) + \mathrm{E}[\varepsilon\varepsilon'] \tag{9}$$

where β_f and β_g are matrices containing the individual coefficients estimated in Equation (6). To statistically test whether factors affect the comovements among the VaR of financial institutions, we first extract the first principal component $\widehat{\Omega}_1$ from the correlation matrix Ξ, derived from $\sum$, following Equations (1) to (3). Then, our two-pass test procedure consists of the following steps. We start by running a time-series OLS regression of the variations in systemic risk $\widehat{\Omega}_{1,t}$, estimated in Equation (2), onto the set of observable factors *f* and *g*:

$$\widehat{\Omega}_{1,t} = \alpha + \delta_f f_t + \delta_g g_t + \varepsilon_t \tag{10}$$

where *f* and *g* are the previously defined set of climate, macroeconomic and market factors. The same assumption about error terms applies (see Equation 6). This regression estimates the effect of an increase in climate risks on simultaneous changes in the downside risk of financial institutions. Unlike Section 2.3, which exploits macro panel data to propose a dynamic estimation of the Climate Exposure CoVaR, we only estimate Equation (10) over the entire period from 2005 to 2022 because of the moderate size of the time series (207 monthly observations).

We then perform a cross-sectional OLS regression of $\widehat{\mathrm{X}}_1$, the loadings of each financial institution *i* to $\widehat{\Omega}_1$ (see Equation 3), onto $\hat{\beta}$ estimated in Equation (6):

$$\widehat{\mathrm{X}}_{1,i} = \alpha + \gamma_f \hat{\beta}_{f,i} + \gamma_g \hat{\beta}_{g,i} + \varepsilon_i \tag{11}$$

This second regression tests whether the financial institutions most exposed to climate risks have stronger tail dependence with the rest of the financial sector. $\hat{\beta}_{f,i}$ and $\hat{\beta}_{g,i}$ represent the individual risk factor exposures estimated over the entire time frame.

We consider that climate risks exacerbate tail dependence among financial institutions if the respective coefficients $\hat{\delta}_f$ and $\hat{\gamma}_f$ are both positive and significant (see Equations 10 and 11). Again, f stands for $\Delta\widehat{VaR}_{BMG}$ and $\Delta\widehat{VaR}_{VMS}$, the tail transition and physical risk factors, respectively. We estimate standard errors based on Newey and West (1987) for time-series regressions (Equations 6 and 10) and White (1980) for cross-sectional regressions (Equation 11). We also estimate Equation (11) with fixed effects for industries and countries and clustered standard errors.

2.5. Data

2.5.1. Stock market data

From Refinitiv Datastream, we obtain an initial list of 21,788 European stocks – 8,750 active and 13,038 dead – including members of the European Union, Norway, Switzerland, and the United Kingdom. We only use common equities, thus excluding preference shares, warrants, closed-end funds, and European depositary receipts. In addition, we focus on the primary market in 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 would have been misclassified as stocks by Datastream. This procedure leads us to remove 1,713 assets from the initial database.

Based on the remaining list, we download prices (including dividends) and compute log returns from the available price series (15,786).[11] We apply several filters recommended by Landis and Skouras (2021) to deal with implausible returns, illiquidity, and unusually high or low volatility. Specifically, we eliminate from our sample the series for which more than 95 %

[11] 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.

of the returns have the same sign (positive or negative). Then, we discard the series for which more than 25 % of the returns are equal to 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 non-financial assets. We use the non-financial assets to construct the climate risk factors, while the financial stocks serve as the input to our systemic risk measure.

2.5.2. 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). Similar to other articles (see e.g., Acharya et al., 2017; Engle et al., 2015), we focus on large financial institutions, as these institutions 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 non-life insurance companies, 111 financial services companies, 71 real estate investment and services firms (REIS), and 24 real estate investment trusts (REIT). The ten most represented countries are the United Kingdom (55), Switzerland (49), France (37), Germany (33), Sweden (27), Italy (25), Belgium (20), Norway (19), Denmark (18), and Poland (18). Table 5 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 of 1.276, a market beta of 0.824, and an average Scope 3 emissions (in tons) to sales (in thousand euros) of 6.798.

2.5.3. Financial and environmental variables

We collect a large set of financial and environmental variables from multiple sources for our sample of 12,283 shares (see the list, definitions, and data sources in Appendix B). 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. Environmental variables are from several sources, namely Refinitiv Datastream, ISS-ESG, Carbone4Finance, CDP, and Bloomberg. Finally, to study the institutional ownership structure of European financial institutions, we use Securities Holdings Statistics, a unique proprietary dataset of the Eurosystem.

2.5.4. Systematic risk factors

We download European Fama and French (2015) and Carhart (1997) factors from Kenneth French's website. The Fama and French (2015) factors comprise the market factor (MKT, returns of the European market portfolio minus the risk-free rate), 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, 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 non-traded version of the liquidity factor (LIQ) of Pástor and Stambaugh (2003), and the quality-minus-junk (QMJ) factor of Asness et al. (2019).[12] The

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

q5 factors include the market excess returns (*MKT*), the size factor (*SMB*), the investment factor (*IA*), the return on equity factor (*ROE*), and the expected growth factor (*EG*).

While the economic content of these factors is an unsettled debate (Kozak et al., 2018)[13], Ang (2014) points out 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 to 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). Table 2 reports limited correlation across the estimated $\Delta\widehat{VaR}$ of all factors, indicating that they reflect non-overlapping information that can help explain the level of systemic risk in the financial sector. $\Delta\widehat{VaR}_{BMG}$ is slightly correlated with $\Delta\widehat{VaR}_{WML}$, $\Delta\widehat{VaR}_{CMA}$, and $\Delta\widehat{VaR}_{HML}$, at 21%, 19%, and -22%, respectively. $\Delta\widehat{VaR}_{VMS}$ is moderately correlated with $\Delta\widehat{VaR}_{WML}$, $\Delta\widehat{VaR}_{DP}$ (see definition below) and $\Delta\widehat{VaR}_{MKT}$, at 26%, 26% and 25%, respectively. The correlation between $\Delta\widehat{VaR}_{BMG}$ and $\Delta\widehat{VaR}_{VMS}$ amounts to -5%.

2.5.5. Economic and financial risk indicators

Besides, we use a battery of macroeconomic and financial variables that might drive the level of systemic risk in the financial sector. 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 et al., 2016). We download the risk reversal on the USD/EUR options from Bloomberg (RR), for which a negative value implies that expectations are skewed toward the depreciation of the euro. Then, we build a series of

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

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 Greece, Ireland Italy, Spain, and Portugal 10-year rates reflects the divergence in rates between countries of the North and the South of the Euro Area (NS). The high yield euro corporate rates against the 3-month Euribor rate represents the default premium (DP). Lastly, we use an economic sentiment (ES) indicator based on surveys from Eurostat. Again, for consistency with the dependent variable in Equations (6) and (10), we estimate the VaR of the financial risk indicators. We make an exception for the risk reversal (RR) because it is an option-based measure whose price is already derived from the volatility of the underlying assets. In addition, we do not estimate the VaR of the economic sentiment (ES), as the procedure does not seem appropriate for an indicator that is not based on market data.

3. Empirical results

3.1. Individual exposures of financial institutions to tail climate risks

This section begins by examining individual financial institution exposures to extreme climate risks using our Climate Exposure CoVaR measure. First, we provide details on the distribution of individual risk exposures by sector and country. It should be noted that the high climate risk exposure of some groups of financial institutions may have a dual origin: acute climate risks, in terms of regulation or natural disasters, or a degraded balance sheet (or other characteristics), which makes the institutions more vulnerable to climate shocks.[14] Second, we

[14] We study the characteristics that interacts with individual climate risk exposures in Section 3.3.

examine the dynamic exposure of financial institutions to climate risks to determine whether the risk exposures have increased over time.

3.1.1. Static estimation

Figure 3 plots the distribution of transition and physical risk exposures of financial institutions estimated in Equation (6). We observe that the distribution of transition risk exposures is skewed to the right, indicating that there is a larger proportion of financial institutions with high transition risk. This positive skewness appears to hold for all types of financial institutions except REIS (see Figure 4, Panel A). It is particularly high for REIT and life insurance, which might be due to the long-term nature of these activities. This skewness also occurs in all European countries, although it is most pronounced in France and the UK (see Figure 5, Panel A). By contrast, financial institutions' exposures to physical risk have a more balanced distribution, albeit with a slight leftward skew, suggesting that investors do not evaluate physical hazards as a tail risk for financial institutions. Negative exposures for some institutions can be explained by the fact that financial institutions face increased demand after natural disasters (e.g., Cortés and Strahan, 2017; Shelor et al., 1992). This trend is visible for all types of financial institutions (see Figure 3, Panel B). Furthermore, the four countries with the highest exposure to physical risks are Germany, Norway, Poland, and Sweden (see Figure 5, Panel B).

Table 6 presents the 30 largest individual exposures to tail transition risk. Among the 30 financial institutions, 11 are from the United Kingdom. The largest exposures are the Bank of Ireland and two REIS institutions, Henry Boot and JM Real Estate, with coefficients of 1.49, 1.71, and 1.36, respectively, meaning that if transition risk worsens by one percentage point, the VaR of Bank of Ireland will deteriorate by 1.49 percentage points. On average within this group, a one-percentage-point decrease in the VaR of the transition risk factor leads to a 0.71 percentage-point decline in the monthly VaR of the financial institutions. This group comprises eleven financial institutions with a market capitalization above €10 billion on average on the entire period, including four banks (Barclays, Danske Bank, Lloyds Banking Group, Skandinaviska Enskilda Banken), three non-life insurers (AXA, Sampo, Swiss Re), two life insurers (Aviva, Legal and General), one financial service institution (Deutsche Boerse), and one REIT (Unibail-Rodamco).

Table 7 reports the 30 largest physical risk exposures, of which eight are Swedish institutions and five are Norwegian institutions. The Lithuanian financial services provider Invalda has the largest exposure to physical risk, with an individual monthly VaR worsening by 5.78 percentage points when physical risk deteriorates by one point.

3.1.2. Dynamic estimation

We now explore the dynamics of financial institutions' exposure to climate risks based on Equation (6). The results show that financial institutions' exposure to transition and physical risks has increased over the past decade (see Figures 6, Panel A and B), primarily after the Paris Agreement in December 2015. Nevertheless, only the transition risk exposures appear positive and significant over the entire period. Focusing our attention on specific sectors (see Figure 7), we show that transition risk exposure has mostly increased for banks and life and non-life insurance companies, with the mean-group coefficient becoming significant around 2015-2017. Our results differ from the contemporaneous paper of Jung et al. (2021) which focuses on banks and does not find an upward trend in their climate risk exposure. This discrepancy could be explained by the fact that we focus on extreme climate risk and use a transition risk factor that includes a large number of firms, while their factor is centered on coal and oil companies. The upward trend is less clear for financial services firms, but we still observe that transition risk exposure became significant after 2017. For the real estate companies, no trend is discernible, but the REITs' exposure to transition risk is positive and significant over the entire period, which is consistent with the results based on the static estimates. With respect to physical risk (see Figure 8), none of the financial industries shows a significant positive exposure, but there is still an upward trend, with the coefficient for most industries becoming insignificantly positive by the end of the period, with the exception of REIS.

3.2. The effect of tail climate risks on systemic risk

This section focuses on the effect of extreme climate risks on systemic risk. In contrast to Section 3.2, which analyzes individual financial institutions' exposures to climate risks, we now test whether climate risks are associated with extreme risk dependence among financial institutions, taking into account potential second-round effects of climate risks in the financial sector.

3.2.1. Time series regressions

Using time-series regressions, we examine in Table 8 whether tail climate risks significantly contribute to tail risk dependence among financial institutions, after taking into account several factors known to be predictors of systemic risk. In Panel A, we run regressions of $\widehat{\Omega}_1$, our indicator of systemic risk capturing common time variations in the VaR of financial institutions, on climate risk factors (BMG for transition risk and VMS for physical risk). Overall, we observe a positive and significant impact of transition risks on systemic risk, while physical risks have no significant effect. We find that a one standard deviation decrease in the VaR of the transition risk factor leads to an increase of about 0.06 standard deviation in systemic risk.[15] These results are robust when we control for MKT, SMB, and HML factors (column 1), when we further include RMW, CMA, and WML (column 2), when we instead control for other macroeconomic and market stress indicators (RR, ML, DP, YC, NS, ES in column 3), and when all regressors are included together (column 4). Besides transition risks, we find that MKT, SMB, HML, WML, DP, and ES are positively and significantly linked to systemic risk in the European financial sector.

Alternatively, in Panel B, we replace Fama and French factors with the q5 factors of Hou et al. (2015) and add *LIQ* and *QMJ* factors to the list of controls.[16] We confirm the previous results for all specifications. In addition to transition risks, we find that MKT, EG, HML, DP, and ES are positively and significantly associated with systemic risk.

Overall, our results indicate that transition risks impact systemic risk in the time series. By contrast, physical risks do not seem to be priced as a systemic risk factor. These results are robust to alternative specifications of the climate risk factors (see Section 2.2). In unreported results, we perform the same exercise based on each financial industry. While the results are broadly consistent, the effect of transition climate risk on systemic risk appears to be stronger for REITs and life insurers. The adjusted R-squared of our specifications is between 0.82 and 0.93, which suggests that the potential biases related to the presence of omitted variables might be limited.

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

3.2.2. *Cross-sectional regressions*

Next, we carry out a cross-sectional analysis in Table 9 to check whether the financial institutions most exposed to climate risks ($\hat{\beta}_{BMG}$ and $\hat{\beta}_{VMS}$) contribute more to the tail dependence in the financial sector ($\hat{X}_1$), after controlling for the exposures to other risk factors. As for time series regressions, we find positive and significant coefficients associated with the exposure to transition risk, while the exposure to physical risk does not seem to affect financial institutions' contribution to global risk (Panel A). 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 country and financial industry, as well as standard errors clustered at the country level (columns 5 to 8). Including fixed effects allows us to show that climate risks also determine the contribution to global downside risk within each financial industry and country. Apart from transition risks, we also show that exposure to MKT, SMB, HML, ML, DP, and ES tends to be positively linked to the contribution of financial institutions to systemic risk. Interestingly, some differences emerge between the results based on the time series and cross-sectional regressions, as illustrated by the effect of ML, the interbank market liquidity indicator, which only appears significant in the cross-sectional regressions. This discrepancy indicates that the two-pass regression procedure is useful to ensure the robustness of the results.

Based on the alternative set of factors, we confirm in Panel B that among climate risks, only the exposure to transition risk appears to have a consistently positive and significant effect on the contribution to systemic risk for all specifications (columns 1 to 8). By contrast, the coefficients associated with physical risk do not exhibit a consistent pattern. Besides, we find positive and significant effects associated with exposure to MKT, ME, ROE, EG, LIQ, QMJ, and YC. We report adjusted R-squared values between 0.27 and 0.43.

Overall, our findings indicate that transition risks positively and significantly contribute to systemic risk, both in the time series and the cross-section dimensions. On the contrary, physical risks do not yet seem to have an impact on systemic risk. This conclusion remains unchanged when we substitute the baseline versions of the climate risk factors with the alternatives described in Section 2.2.[17]

3.3. Individual characteristics of financial institutions and tail climate risks

In this section, we investigate which institution-level characteristics are associated with the exposure to tail climate risks. We report our results in Table 10 in the case of transition risks. We start by regressing individual (statically estimated) exposures to transition risks (see Equation 6) on the natural logarithm of market capitalization, net income, market-to-book, cash, and equity market beta. Our results, reported in column (1), indicate that market capitalization, profitability, and equity beta are positively associated with individual exposures to transition risk. This finding is consistent with the climate risk stress test of the European Central Bank showing that large institutions tend to be more exposed to the most emitting sectors.[18] By contrast, tail transition risk is negatively correlated with cash levels, suggesting that they may have less liquidity to deal with the effects of climate shocks on portfolios. We then confirm these results in column (2) after including country and industry fixed effects. We introduce dynamically estimated exposure coefficients in column (3), allowing us to include year fixed

[17] Contrary to carbon emissions in the case of transition risk, there is no raw indicator consensually capturing physical risk. Therefore, we rely on third-party physical risk ratings to construct our physical risk factor. We acknowledge this could affect our findings on physical risk (see Section 2.2).

[18] 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.

effects. Our results confirm that larger financial institutions tend to be more exposed to transition risks.

Next, we augment our regressions with additional extra financial characteristics and assess their association with transition risk exposure after controlling for year and institution-level fixed effects. We first investigate the impact of Scope 3 CO2 emissions (CO2 emissions indirectly emitted by financial institutions, primarily through their investment and loan portfolios, divided by their revenue in million dollars) [19]. We find that Scope 3 emission intensity is negatively associated with the exposures to transition risk, indicating that financial institutions with cleaner credit and market portfolios are less exposed to transition climate risk (column 4). Exposure to tail transition risk is also lower for institutions with third-party verified Scope3 emissions (column 5) and for institutions reaching their emission reduction targets (column 6), suggesting that both information reliability and emission reduction trajectories are considered in investors' risk assessment. In column (7), we investigate the relationship between the long-term incentives given to board members and transition risks. We find that exposures to transition risk are significantly lower when board members have long-term incentives, which indicates that long-termism can help reduce transition risk.[20] Finally, we assess the association between transition risks and financial institutions' ownership structure. We find that financial institutions with larger institutional ownership have a lower exposure to transition risk (column 8). This result could be explained by the fact that institutional investors tend to have long-term portfolios, and therefore the long-term considerations of institutional owners would increase

[19] For example, for the banks, Scope 3 emissions mainly correspond to emissions linked to corporate financing, property investments, and loans granted to clients. For real estate activities, Scope 3 emissions are estimated from the energy consumed in the operation of buildings owned or managed by the company.

[20] These results are related to the findings of the climate risk 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."*

portfolio firms' awareness on long-term issues such as climate risks (see Dyck et al., 2019 and Chen et al., 2020 in the case of CSR activities).

In Table 11, we examine which institution-level characteristics correlate with higher exposure to physical risks. Financial institutions with higher exposures to physical risks have a lower market capitalization, and higher equity beta (columns 1 and 2). Thus, small financial institutions appear to be more exposed to physical risk, which can be explained by a lesser geographical diversification of their assets compared to large institutions. Physical risks also tend 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 insignificant.

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

3.4. Tail climate risk and adaptation measures

According to previous results, tail climate risks influence systemic risk within the financial sector. In this section, we investigate whether financial institutions take action to adapt to tail climate risks. Our results are reported in Table 12.

In Panel A, we assess the impact, if any, of tail transition risk on managers' disclosure of ESG and climate information, as well as carbon offsetting, carbon allowance trading, an engagement with policymakers on climate-related issues. According to Campbell et al. (2014), firms are more likely to disclose information about a risk when they are materially exposed to it. Moreover, Yu et al. (2020) suggest that "greenwashers" can be identified as firms that disclose large amounts of ESG data but have poor ESG performance. Under this definition, a positive association between transition risk exposure and ESG or climate disclosure raises the question of possible greenwashing by financial institutions. Furthermore, using carbon offsetting to decrease net carbon emissions or engaging with policymakers are plausible forms of transition risk management.

In column (1), we start by analyzing the Management Discussion and Analysis (MD&A) section, providing managers' key comments on the annual reports. The MD&A section is seen as allowing communication in a flexible manner (Brown et al., 2021). We assess whether higher transition risk increases the probability to integrate ESG information in the MD&A section, after controlling for the natural logarithm of market capitalization, net income, market-to-book, cash, beta, ESG disclosure score, as well as industry-year and country-year fixed effects.[21] All our control variables are lagged by one year to mitigate potential endogeneity issues. Then, in column (2), we more specifically assess whether transition risk increases the propensity to discuss climate risk in the MD&A section. Across our specifications, our findings indicate a positive and significant effect of tail transition risks on the disclosure by managers of ESG and climate information, after controlling for various determinants of ESG disclosure. A one standard deviation increase in tail transition risks is associated with a 1.9 to 2.6 percentage point increase in the probability to disclose ESG and climate information in the MD&A section. We

[21] 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 in the management report (MD&A), and the NFRD does not explicitly mention climate matters (see here).

consider in column (3) whether these results translate into a higher environmental transparency. We find that, all else equal, exposure to transition risks significantly decreases environmental transparency. Overall, these results indicate that transition risks lead managers to disclose information through the MD&A section, a flexible communication channel, allowing to pursue a strategy of selective environmental disclosure. This selective environmental disclosure strategy might be an attempt to greenwash.

In column (4), we further find that all else equal, financial institutions with higher levels of transition risk engage more in carbon offsetting. This result is consistent with a risk management perspective, whereby financial institutions would try to decrease their transition risk exposure by lowering their net carbon emissions through carbon offsetting. One caveat of this test is that our measure does not distinguish between the different types of carbon offsetting. Nonetheless, we can reasonably expect that these carbon offsets primarily pertain to Scope 3 emissions, as Scope 3 emissions represent the vast majority of financial institutions' carbon emissions.[22] Finally, we find in column (5) that institutions with higher exposure to tail transition risk are less likely to engage with policymakers on possible responses to climate change. This result provides evidence against the view that climate regulation would be captured by the riskiest financial institutions. In a similar vein, the findings of Schneider et al. (2023) indicate that the larger trading banks (i.e., those most likely to be "Too Big to Fail") face the toughest stress tests, a result they interpret as going against regulatory capture concerns.

As our results reported in the previous sections indicate that investors do not consider physical risk as material for financial institutions over our sample period, we do not expect that physical risk should significantly impact ESG and climate disclosure. However, as most

[22] 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.

investors expect physical risk to become material within a few years (Krueger et al., 2020), financial institutions might already take action to face it. In Panel B, we, therefore, analyze the impact of tail physical risk on financial institutions' efforts to diminish their environmental footprint. We start by assessing the impact of physical risk on their resource use efficiency score. The results are reported in column (1) and indicate that a one-standard-deviation increase in physical risk generates a 1.8 point increase in the resource use efficiency score.[23] We then turn to the effect of various initiatives aiming to minimize financial institutions' environmental footprint. We analyze the impact of physical risk on the creation of an internal team of environmental specialists (column 2), the launching of environmental products (column 3), and the use of climate scenario analysis (column 4). Our results indicate that a one-standard-deviation increase in physical risk leads to a 3.3 to 4.8 percentage point increase in the probability of engaging in such initiatives. Finally, we find that financial institutions with higher exposure to physical risk are more likely to engage with their suppliers on climate change issues. Note that, contrary to nonfinancial disclosure readily available to investors or an immediate lowering of net carbon emissions through offsetting, these internal initiatives create a structure that might only have effects in the long run. This differentiated response might stem from the fact that investors consider transition risks as a more immediate threat than physical risks (Krueger et al., 2020; Stroebel and Wurgler, 2021).

Finally, in unreported robustness tests, we verify that all the results documented in Table 12 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 tail climate risks influence

[23] The resource efficiency score goes from 0 (worst) to 100 (best).

financial institution' disclosure strategy and their propensity to engage in various initiatives aiming to minimize their environmental footprint.

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 paper, we develop a framework for analyzing systemic climate risks based on environmental and stock market data. We then apply our approach to a sample of Europe's largest financial institutions. We find that many financial institutions are positively and significantly exposed to transition risk, in particular life insurers and real estate investment trusts. Moreover, we reveal that the exposure to transition risk has increased continuously since 2015, mainly for banks, life, and non-life insurance companies. Finally, our article shows that transition climate risk can exacerbate tail dependence among financial institutions, which is a key aspect of systemic risk. By contrast, we do not find evidence of such contagion effects in the case of physical climate risk.

Besides, our results show that climate risk exposure is lower for financial institutions committed to environmental risk management and for those providing long-term incentives to board members. We also highlight that financial institutions with cleaner investment and lending portfolios tend to be less exposed to transition risks. In a nutshell, our findings suggest that regulators and managers of financial institutions have levers to reduce systemic climate risks. Since climate risks appear to affect both individual risk and tail dependence within the financial sector, we argue that the characteristics we find associated with exposure to climate risks may be of interest to microprudential and macroprudential regulations.

Our proposed market-based framework is more responsive than other accounting-based models and can be used to dynamically monitor the prevalence of systemic climate risks. We argue 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. Therefore, our results could also be factored into 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 could be applied to other countries, sectors, asset types, or periods. In particular, it could also be used to assess the influence of other emerging threats to financial stability, such as cybersecurity risk, provided that series representing time variations in the risk source are available. However, two caveats apply. First, our results must be interpreted with some caution, as they primarily reflect the extent to which investors perceive the effect of climate risks on financial stability. Second, we cannot disentangle between the different channels of contagion, namely common risk exposures, spillover effects, and pure contagion, which may represent a fruitful area for future research.

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Appendix A: 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. Existing articles estimate asset comovements based on returns, volatility, and VaR (e.g, Diebold and Yilmaz, 2009; Adams et al., 2014; White et al., 2015). Table 1 shows that the interconnections between financial institutions are different whether we estimate comovements based on returns or VaR to identify them. Measuring comovements among tail risk indicators seems better suited to capture systemic risk than relying on return comovements.

The VaR is the estimated loss of a financial institution that, within a given period, will not be exceeded with a certain probability θ. Thus, if θ is equal to 95 %, the 1-month θ-VaR shows the negative return that will not be exceeded within this month with a 95 % probability:

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

VaR can be estimated dynamically based on Equation (A.2):

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

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 pre-specified distribution and $\hat{\mu}_{i,t}$ is the mean returns 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 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 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 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 (8) is positive for 286 financial institutions, and positive and significant at the 5% level for 107 series out of 371.

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

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

All the parameters (μ, ω, α, γ, and β) are estimated simultaneously, by maximizing the log-likelihood.

Table A.1 tests 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 different 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 to alternatives. This finding is consistent with the work of Brownlees et al. (2011), which shows that the GJR-GARCH model works best to forecast stock volatility. Since we are primarily interested in tail risk measurement, we now turn our attention to the result 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 VaR exceedances. We show that the GJR-GARCH model seems appropriate to reflect the level of tail risk of financial institutions.[24] 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. It also leads to the lowest number of rejections in the Christoffersen et al. (2001) test. 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 heavier-tailed error distribution.

Table A.1

Model selection.

This table performs diagnostic tests for model selection and error distribution assumptions (see Equation A.3). Panel A reports the information criteria of Akaike, Bayes, Shibata, and Hannan Quinn. Panel B runs the 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). GJR-GARCH, E-GARCH, NA-GARCH, and C-GARCH respectively stand for the model of Glosten et al. (1993), the Exponential GARCH model of Nelson (1991), the Nonlinear Asymmetric GARCH model of Engle and Ng (1993), and the component GARCH of Engle and Lee (1999).

Panel A: Information criteria

Model	Error distribution	Akaike	Bayes	Shibata	Hannan Quinn
	Normal	6,925	7,006	6,924	6,958
	Skew-normal	6,909	7,005	6,908	6,948
	Student	6,820	6,917	6,819	6,859
	Skew-student	6,816	6,929	6,814	6,862
GJR-GARCH	Generalized error	**6,814**	**6,910**	**6,812**	**6,852**
	Skew-generalized error	6,818	6,931	6,816	6,864
	Normal inverse gaussian	6,823	6,935	6,820	6,868
	Generalized Hyperbolic	6,827	6,955	6,824	6,878
	Johnson's SU	6,818	6,931	6,816	6,864
GARCH		6,943	7,023	6,942	6,976
GJR-GARCH		**6,909**	**7,005**	**6,908**	**6,948**
E-GARCH	Skew-normal	6,923	7,019	6,921	6,961
NA-GARCH		7,216	7,312	7,214	7,255
CS-GARCH		6,956	7,068	6,954	7,001

[24] Potential alternatives would be the exponential GARCH model of Nelson (1991) or the component GARCH of Engle and Lee (1999).

Panel B: VaR exceedance tests

Model	Error distribution	Expected VaR 5% exceed	Realized VaR 5% exceed	Standard deviation around 10	Number of rejections		
					VaR UC test	VaR CC test	VaR Duration test
GJR-GARCH	Normal	10	10,33	2,67	3	7	9
	Skew-normal	10	9,72	**2,31**	6	**4**	12
	Student	10	11,34	3,59	8	11	11
	Skew-student	10	10,77	2,83	**2**	5	**6**
	Generalized error	10	10,67	5,88	14	14	13
	Skew-generalized error	10	9,64	2,71	5	9	9
	Normal inverse Gaussian	10	**10,03**	2,41	**2**	5	9
	Generalized Hyperbolic	10	12,44	8,01	25	25	17
	Johnson's SU	10	10,40	2,90	**2**	5	9
GARCH	Skew-normal	10	**9,90**	2,40	5	16	8
GJR-GARCH		10	9,72	2,31	6	**4**	12
E-GARCH		10	9,48	**2,25**	2	6	8
NA-GARCH		10	10,14	9,97	6	13	9
CS-GARCH		10	10,08	2,38	**1**	6	11

Appendix B: Variable description

Panel A: Risk factors

Variable	Description
BMG	Transition risk factor, constructed as a long-short portfolio based on both estimated and reported carbon emission data (scopes 1 & 2) for all dead and active stocks reported in Refinitiv Eikon and listed on European equity markets (excluding financial sector companies). Alternatively, we build the factor from Scope 1 emissions only.
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	Non-traded 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 Carbone 4.
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).

Panel B: Financial and extra-financial characteristics

Variable	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).
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).
Environmental Disclosure 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).
ESG Disclosure Score	Score based on the extent of a company's Environmental, Social, and Governance (ESG) disclosure. The score ranges from 0 for companies that do not disclose any of the ESG data included in the score, to 100 for those that disclose every data point (ESG_DISCLOSURE_SCORE in Bloomberg).
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 extra-financial 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).
LowScope3intensity	Dummy variable equal to one if the financial institution's Scope3 emissions to revenues (in million USD) ratio is in the bottom quartile (from item in Datastream).
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 emissions reduction target during the year (from CDP, item CDP_EMISS_RED_TGT_REACHED_OR_CP in Bloomberg).
ResourceScore	Resource score, reflecting the financial institution's performance and capacity to reduce the use of materials, energy, or water, and to find more eco-efficient solutions (item TRESGENRRS in Datastream).
SupplierClimateEngagement	Dummy variable equal to one if the financial institution engages with its suppliers on climate change issues (from CDP, item CDP_VALUE_CHAIN_ENGAGEMENT in Bloomberg).
TradingAllowances	Dummy variable equal to one if the financial institution participates in the European Union Emission Trading Scheme (from CDP, item CDP_TRADING_ALLOWANCES_ETS 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).

Appendix C: Figures and Tables

Figure 1

Time variations in systemic risk.

The indicator represents the first principal component $\widehat{\Omega}_1$, extracted from Equations (2) and (3), and accounts for the common variations in the VaR of financial institutions. The chart on the left is in levels (January 2005 = 100), while the chart on the right is in first difference.

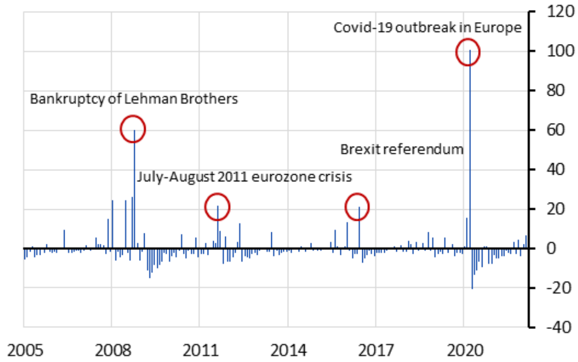


Figure 2

Cumulative returns of the climate risk factors

The figure represents the cumulative returns of the climate risk factors (January 2005 = 100), built based on Equations (4) and (5). The chart on the left (right) plots the returns of the transition (physical) risk factor.

Figure 3

Distribution of climate risk exposures of financial institutions.

The figure represents the distribution of the vectors of financial institutions' exposures to climate risks, $\hat{\beta}_{BMG}$ (chart on the left) and $\hat{\beta}_{VMS}$ (chart on the right), estimated in Equation (6).

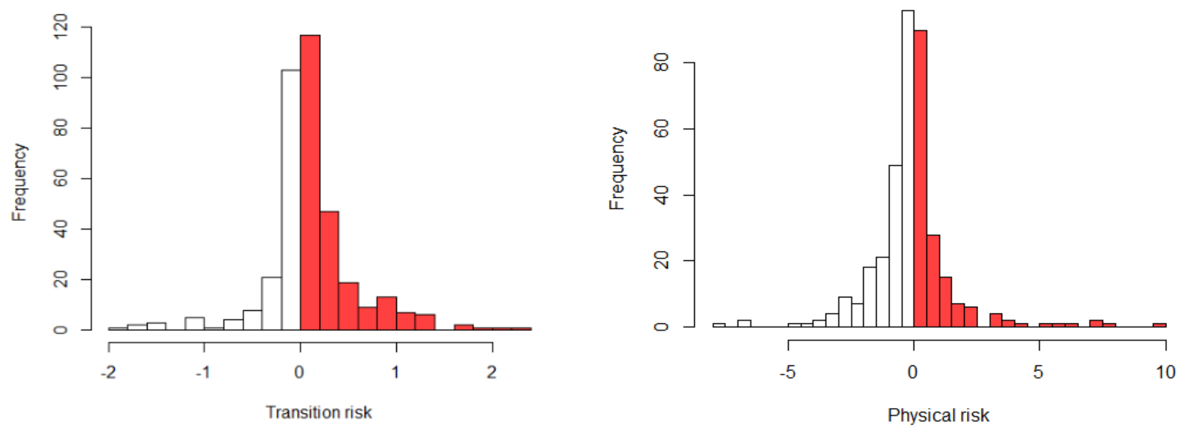
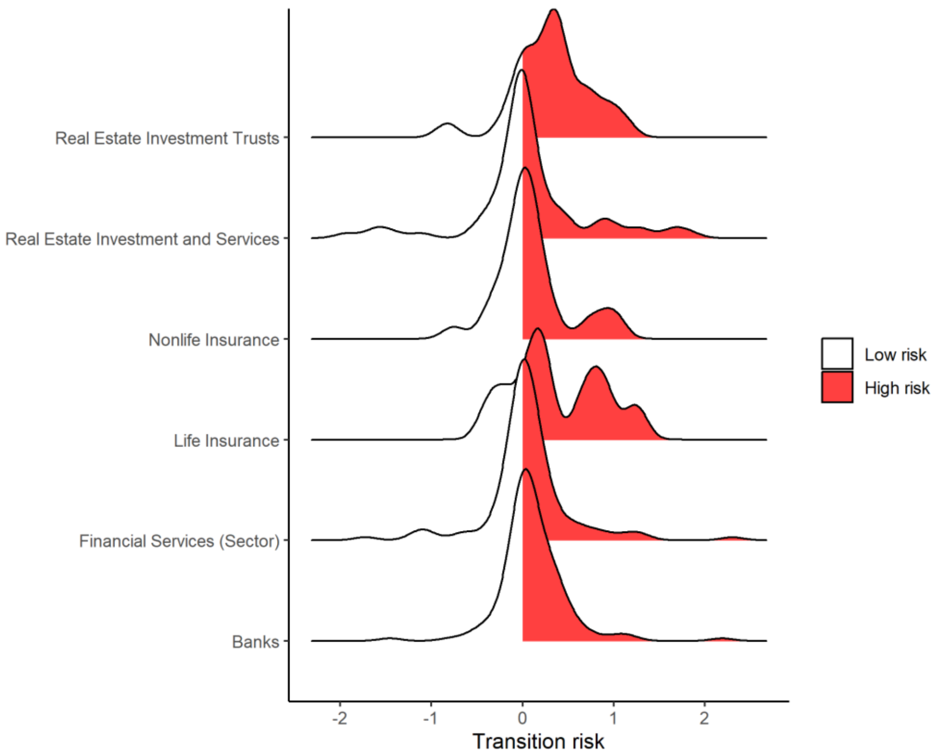


Figure 4

Distribution of climate risk exposures by type of financial institutions.

The figure represents the distribution of the vectors of financial institutions' exposures to climate risks, $\hat{\beta}_{BMG}$ and $\hat{\beta}_{VMS}$, estimated in Equation (6), based on a density function. Panel A provides details by type of financial institution for $\hat{\beta}_{BMG}$, the transition risk exposure indicator. Panel B provides details by type of financial institution for $\hat{\beta}_{VMS}$, the physical risk exposure indicator.

Panel A: Transition risk exposure



Panel B: Physical risk exposure

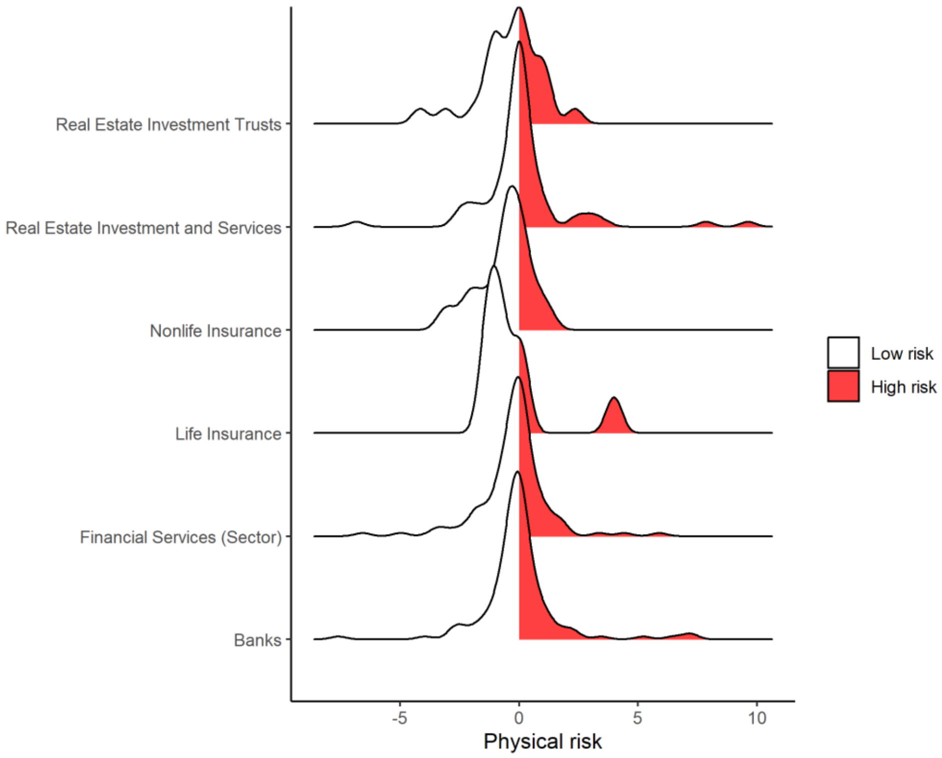
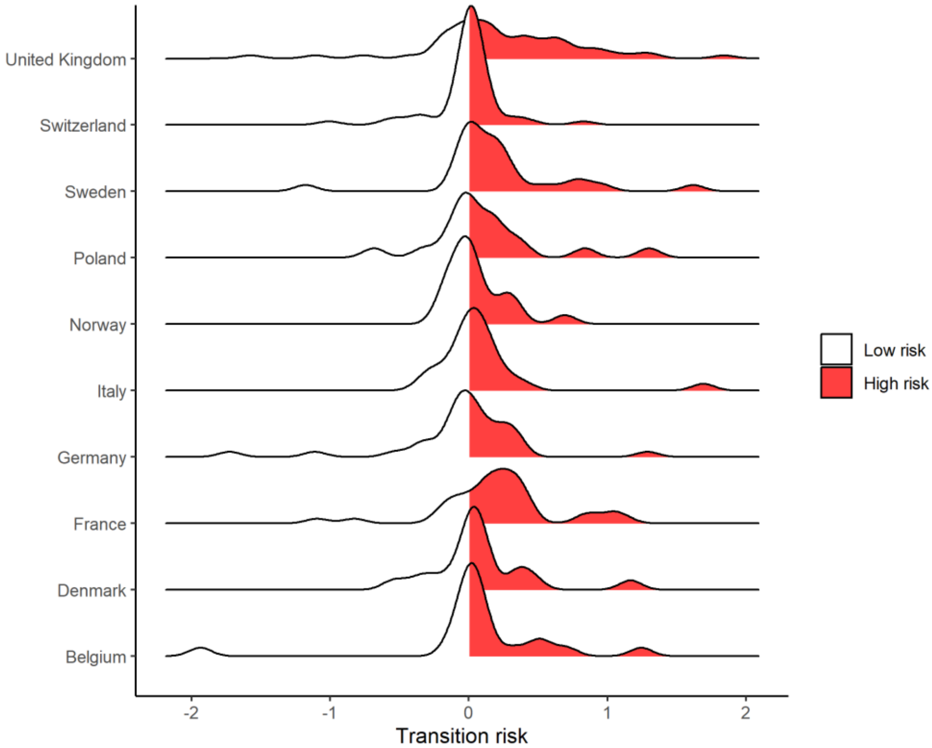


Figure 5

Distribution of climate risk exposures by country

The figure represents the distribution of the vectors of financial institutions' exposures to climate risks, $\hat{\beta}_{BMG}$ and $\hat{\beta}_{VMS}$, estimated in Equation (6), based on a density function. We focus on the ten most represented countries in our sample of 371 financial institutions, namely the United Kingdom (55), Switzerland (49), France (37), Germany (33), Sweden (27), Italy (25), Belgium (20), Norway (19), Denmark (18), and Poland (18). Panel A provides details by country for $\hat{\beta}_{BMG}$, the transition risk exposure indicator. Panel B provides details by country for $\hat{\beta}_{VMS}$, the physical risk exposure indicator.

Panel A: Transition risk exposure



Panel B: Physical risk exposure

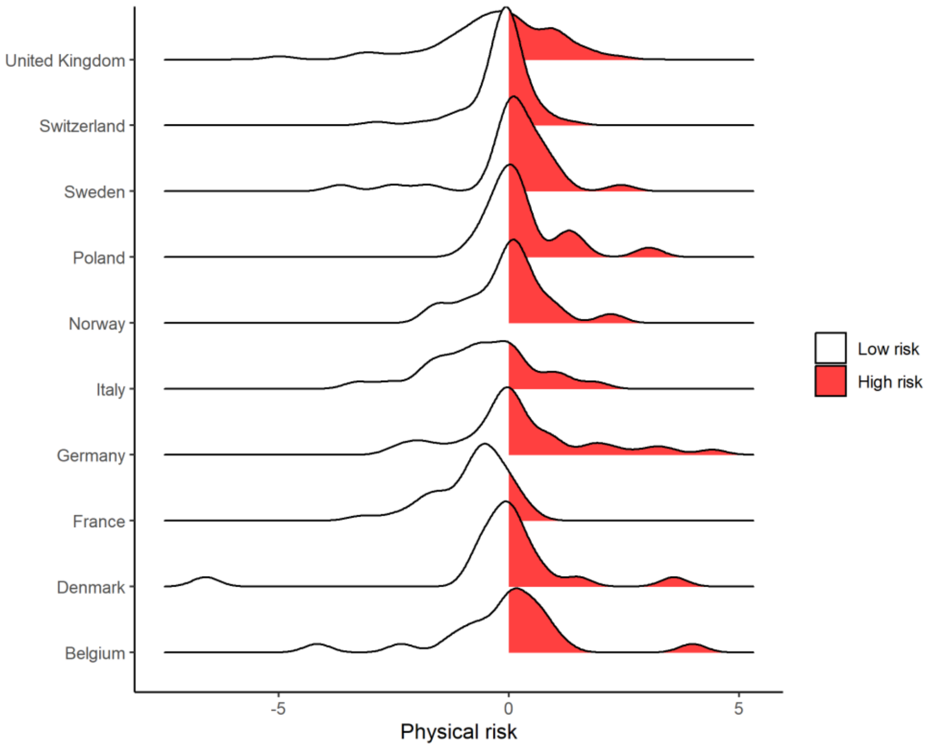
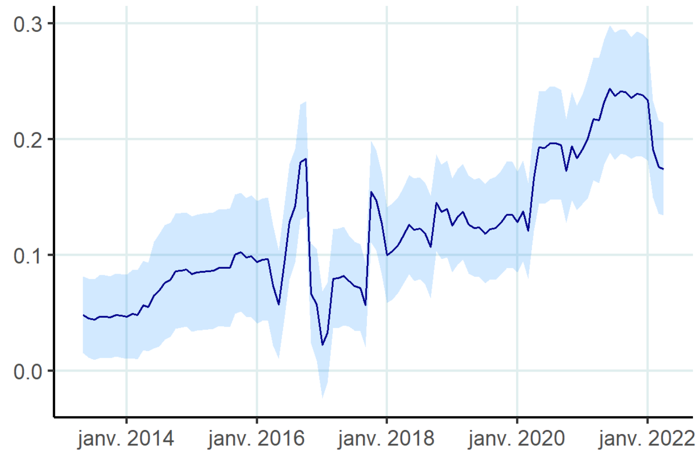


Figure 6

Dynamic climate risk exposures for all financial institutions

The figure represents the average dynamics of financial institutions' exposures to transition risks, estimated in Equation (6). To obtain dynamic individual coefficients, we estimate the model dynamically based on rolling windows of 100 observations. Next, we compute the cross-sectional mean (dark blue line) and the 95% confidence interval (blue area) at each period. We use the mean-group estimator (Pesaran, 1995) based on a robust regression of individual estimates on a single cross-section unit. Panel A provides details for $\hat{\beta}_{BMG}$, the transition risk exposure indicator. Panel B provides details for $\hat{\beta}_{VMS}$, the physical risk exposure indicator.

Panel A: Transition risk exposure



Panel B: Physical risk exposure

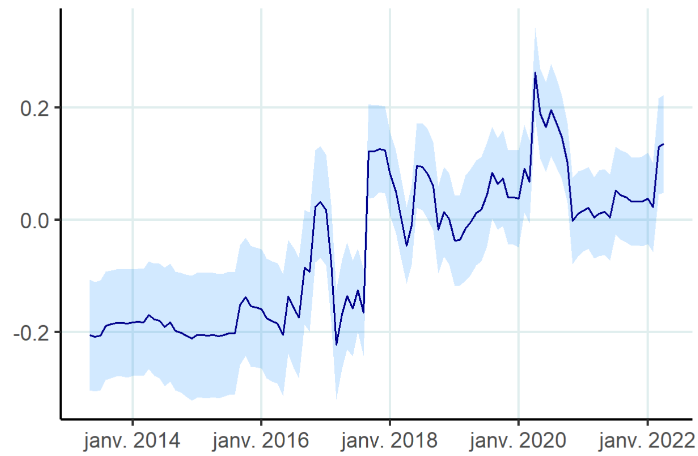


Figure 7

Dynamic transition risk exposures by type of financial institutions

The figure represents the average dynamics of financial institutions' exposures to transition risks, $\hat{\beta}_{BMG}$ estimated in Equation (6). 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 (blue area) at each period. We use the mean-group estimator (Pesaran, 1995) based on a robust regression of individual estimates on a single cross-section 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 8

Dynamic physical risk exposures by type of financial institutions

The figure represents the distribution of the vectors of financial institutions' exposures to physical risks, $\hat{\beta}_{VMS}$, estimated in Equation (6). 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 (blue area) at each period. We use the mean-group estimator (Pesaran, 1995) based on a robust regression of individual estimates on a single cross-section 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.

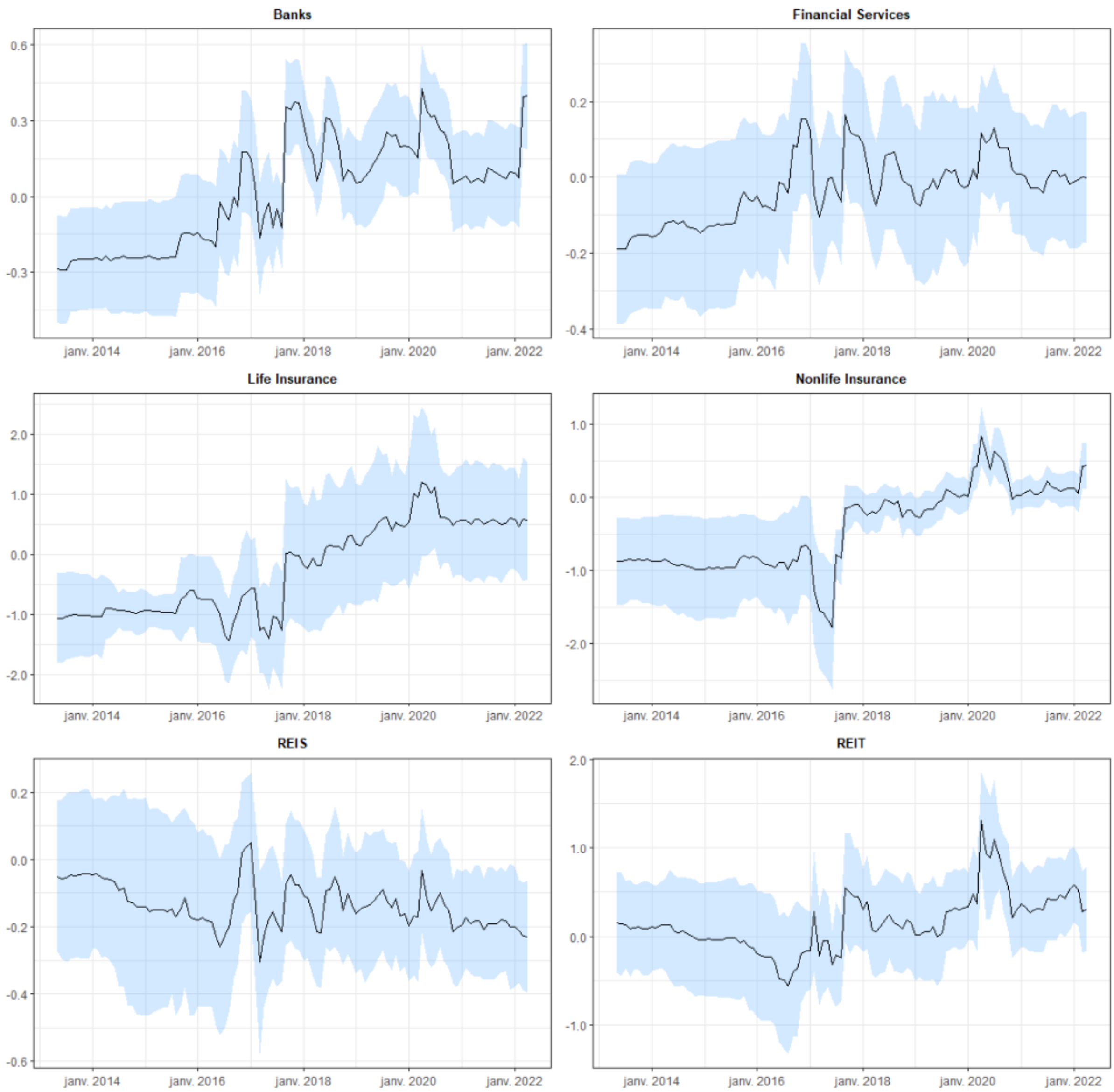


Table 1

Most interconnected institutions based on VaR and returns.

This table reports a list of the most interconnected institutions based on VaR and returns using the loading of each financial institution $\hat{X}_1$ on the first principal component $\hat{\Omega}_1$. 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	Sector	$\hat{X}_1$	Financial institutions	Sector	$\hat{X}_1$
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 2

Correlation matrix for risk factors.

This table presents the correlation matrix among the $\Delta\widehat{VaR}$ of the risk factors. Appendix B presents 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 3

Response of climate risk factors to climate shocks

This table reports the average returns of our climate factors conditional on the value of various climate shock indicators, namely abnormal temperatures, total damages caused by natural disasters, and climate news.

Natural Disasters			
Quantile	Climate shock indicator value	Conditional average	Physical factor returns (%)
0,05	0		0,12
0,1	0	Inferior to	0,12
0,5	10000		0,12
0,5	10000		-0,33
0,9	1910000	Superior to	-0,62
0,95	3593752		-0,83
Abnormal temperatures			
Quantile	Climate shock indicator value	Conditional average	Transition factor returns (%)
0,05	-0,29		0,34
0,1	0,37	Inferior to	0,22
0,5	1,30		-0,09
0,5	1,30		-0,48
0,9	2,47	Superior to	-0,79
0,95	2,91		-1,14
Climate news			
Quantile	Climate shock indicator value	Conditional average	Transition factor returns (%)
0,05	-0,71		1,98
0,1	-0,64	Inferior to	1,70
0,5	-0,17		-0,30
0,5	-0,17		-0,31
0,9	0,78	Superior to	-0,08
0,95	0,96		-0,75

Table 4

Descriptive statistics of climate risk factor constituents.

This table reports the summary statistics of the climate risk factor constituents. **Panel A** presents the descriptive statistics for observations used in the transition risk factor. The transition risk factor is constructed as a long-short portfolio based on estimated carbon emission data (scopes 1 & 2) for all dead and alive stocks reported in Refinitiv Eikon and listed on European equity markets (excluding financial sector companies) between 2005 and 2022. The portfolio is long on the high climate risk firms (>80th percentile) and short on the low climate risk firms (<20th percentile).

Panel A: Transition risk factor

Sectors	Number of firms		% in portfolio		Average market capitalization (in million euros)		Average CO2 emissions (scopes 1 & 2), in tons		Average carbon 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	Low climate risk	High climate risk	Low climate risk	High climate risk
Aerospace and Def.	1	1	0.0%	0.2%	222	4,708	700	164,478	0.42%	655%
Alternative Energy	5	6	0.6%	0.1%	3,035	327	10,856	389,836	0.27%	1105%
Automobiles		3		0.2%		1,626		446,032		22%
Beverages	1	1	0.1%	0.0%	2,471	593	88	70,292	0.02%	15%
Chemicals	1	27	0.3%	7.5%	8,810	7,792	11,664	4,024,673	0.34%	65%
Construction and Mat.	7	15	0.1%	2.2%	491	4,069	4,038	2,551,726	0.34%	145%
Electricity	3	31	0.1%	14.1%	1,017	12,818	107	11,585,986	0.10%	147%
Electronic Equipment	7	1	0.2%	0.1%	654	1,935	1,881	485,900	0.39%	41%
Fixed Line Telecom.	7	6	1.5%	0.6%	5,683	2,886	10,713	410,112	0.30%	40%
Food and Drug Retail	6		1.0%		4,228		10,285		0.27%	
Food Producers		19		2.2%		3,202		6,839,202		610%
Forestry and Paper	1	14	0.0%	1.7%	181	3,460	0	1,237,697	0.00%	59%
Gas, Water	1	12	0.0%	7.4%	740	17,428	1,842	24,236,625	0.51%	118%
General Industrials	2	18	0.3%	1.9%	3,294	2,927	7,725	2,668,725	0.49%	52%
General Retailers	38	2	4.8%	0.0%	3,308	575	10,776	174,412	0.27%	21%
Health Care	12	5	1.7%	0.6%	3,626	3,465	2,760	183,066	0.29%	38%
Household Goods	9	2	0.7%	0.1%	2,034	710	5,293	174,499	0.31%	27%
Industrial Engineering	3	2	0.6%	0.1%	4,957	725	26,792	249,862	0.35%	33%
Metals and Mining		19		2.7%		4,066		13,357,855		12,425%
Industrial Transport.	6	28	1.4%	3.8%	6,606	3,783	36,081	2,621,499	0.34%	181%
Leisure Goods	4		0.2%		1,211		819		0.24%	
Media	33	1	5.8%	1.3%	4,559	35,388	7,286	114,084	0.29%	37%
Mining		35		13.4%		10,782		3,941,549		2,424%
Oil and Gas Prod.		41		24.9%		17,112		7,072,139		121%
Oil Equipment	2	18	0.2%	1.9%	2,639	2,937	290	1,069,231	0.10%	113%
Personal Goods	13	3	25.5%	0.1%	50,977	554	44,366	963,673	0.29%	29%
Pharmaceuticals	12	9	9.4%	1.9%	20,230	5,827	8,767	100,642	0.22%	62%
Software	105	4	15.5%	0.1%	3,823	1,020	3,324	1,241,990	0.31%	1138%
Support Services	22	6	1.9%	0.4%	2,262	1,793	8,700	574,565	0.23%	53%
Technology Hardware	14	3	2.2%	0.1%	4,061	1,328	11,540	217,997	0.27%	34%
Travel and Leisure	15	30	1.9%	3.4%	3,240	3,185	7,804	2,677,820	0.25%	105%
Unclassified	80	48	24.1%	7.2%	7,804	4,247	6,760	8,382,608	0.26%	204%
Total	410	410	100%	100%	6,331	6,866	8,136	5,539,677	0.28%	934%

Panel B presents the descriptive statistics for observations used in the physical risk factor. The physical risk factor is constructed as a long-short portfolio based on Trucost physical climate risk scores for all dead and alive stocks reported in Refinitiv Eikon and listed on European equity markets (excluding financial sector companies) between 2005 and 2022. The portfolio is long on the high climate risk firms (>80th percentile) and short on the low climate risk firms (<20th percentile).

Panel B: Physical risk factor

Sector	Number of stocks		% of portfolio		Average market capitalization (in million euros)		Average physical score (moderate 2050)	
	Low climate risk	High climate risk	Low climate risk	High climate risk	Low climate risk	High climate risk	Low climate risk	High climate risk
Aerospace and Defense	2	7	0.9%	1.5%	2,319	5,305	30.5	61.9
Alternative Energy	4	6	0.6%	0.0%	785	138	34.5	67.3
Automobiles and Parts	6	2	1.2%	0.0%	995	144	33.0	71.0
Beverages	8	3	2.6%	0.7%	1,606	5,267	33.1	62.0
Chemicals	7	10	0.9%	4.2%	619	10,147	33.6	62.2
Construction and Materials	18	16	2.4%	1.1%	659	1,640	33.0	61.6
Electricity	5	2	0.3%	0.7%	261	7,948	31.8	62.0
Electronic and Electrical Equipment	5	3	1.0%	0.0%	1,022	320	31.0	68.0
Fixed Line Telecommunications	4	5	2.0%	1.2%	2,490	5,601	28.5	60.6
Food and Drug Retailers	4	3	1.7%	0.1%	2,161	690	32.8	62.7
Food Producers	18	15	6.9%	0.5%	1,903	834	31.8	64.3
Forestry and Paper	5	3	2.5%	0.2%	2,455	1,404	32.4	61.3
Gas, Water and Multiutilities		3		0.4%		3,544		62.7
General Industrials	13	11	1.2%	1.0%	473	2,193	32.2	63.5
General Retailers	21	6	5.8%	0.0%	1,354	170	32.7	61.3
Health Care Equipment and Services	17	11	4.1%	3.4%	1,197	7,343	32.8	60.2
Household Goods and Home Construction	16	7	3.6%	0.4%	1,126	1,360	33.0	61.9
Industrial Engineering	12	6	3.0%	0.6%	1,227	2,576	33.5	62.7
Industrial Metals and Mining	7	4	0.8%	0.1%	598	725	30.4	63.0
Industrial Transportation	15	16	14.6%	4.1%	4,799	6,189	32.7	64.4
Leisure Goods	6	5	0.2%	0.3%	202	1,431	31.8	62.0
Media	4	24	0.1%	4.1%	85	4,101	29.8	62.1
Mining	15	21	0.3%	0.1%	105	103	31.7	63.0
Oil and Gas Producers	11	9	2.9%	10.8%	1,321	28,821	33.0	64.0
Oil Equipment and Services	7	6	0.4%	0.2%	292	809	30.3	65.7
Personal Goods	3	7	1.0%	0.5%	1,691	1,868	35.0	64.3
Pharmaceuticals and Biotechnology	39	25	7.4%	12.3%	941	11,777	31.3	62.2
Software and Computer Services	31	37	4.3%	7.8%	687	5,072	30.8	61.1
Support Services	11	16	1.7%	4.3%	772	6,406	33.9	62.0
Technology Hardware and Equipment	25	16	2.2%	3.9%	427	5,875	32.1	61.8
Travel and Leisure	12	22	5.9%	2.4%	2,432	2,612	32.1	61.2
Unclassified	89	92	17.2%	32.9%	954	8,565	31.2	62.1
Total	440	419	100%	100%	1,123	5,723	32.0	62.4

Table 5

Descriptive statistics of financial institutions.

This table reports the summary statistics of the financial institutions in our sample. Appendix B presents variable definitions. The sample comprises all European financial institutions from 2005 to 2022, with a market capitalization above €100 million on average over the entire period.

	N	Mean	SD	Median	P25	P75
$\hat{\beta}_{VMS}$	6,350	-0.120	1.564	-0.034	-0.664	0.251
$\hat{\beta}_{BMG}$	6,350	0.081	0.385	0.025	-0.072	0.222
LogMarketValue	6,350	6.454	2.128	6.395	4.836	7.918
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
Cash	6,350	0.046	0.092	0.006	0.000	0.047
Beta	6,350	0.824	0.559	0.760	0.392	1.175
LowScope3intensity	1,842	6.798	8.232	0.864	3.388	10.934
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
TradingAllowances	777	0.313	0.464	0.000	0.000	1.000
PolicyEngagement	1,700	0.747	0.435	1.000	0.000	1.000
ResourceScore	2,186	61.584	29.905	69.105	38.240	87.750
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
SupplierClimateEngagement	800	0.928	0.259	1.000	1.000	1.000

Table 6

Transition risk exposures.

This table presents the Top 30 institutions with large and significant exposures to BMG_t, our transition risk factor. Heteroskedasticity-robust standard errors are reported in parentheses. ***, **, and * indicate significance at the 1%, 5% and 10% levels, respectively. The acronyms REIT and REIS stand for "Real Estate Investment Trusts" and "Real Estate Investment Services", respectively. The Code corresponds to the Datastream identifier.

Financial institutions	Code	Sector	Country	$\hat{\beta}_{BMG}$	
Bank of Ireland Group	IE:BIRG	Banks	Ireland	1.49*	(0.87)
Lloyds Banking Group	LLOY	Banks	United Kingdom	0.70**	(0.34)
Barclays	BARC	Banks	United Kingdom	0.67**	(0.31)
Skandinaviska Enskilda Banken A	W:SEA	Banks	Sweden	0.51**	(0.23)
Banco de Sabadell	E:BSAB	Banks	Spain	0.44*	(0.24)
Groenlandsbanken	DK:GRO	Banks	Denmark	0.32*	(0.19)
Danske Bank	DK:DAB	Banks	Denmark	0.31*	(0.17)
Intermediate Capital Group	ICP	Financial Services	United Kingdom	0.94**	(0.37)
Bure Equity	W:BURE	Financial Services	Sweden	0.73*	(0.43)
Sofina	B:SOF	Financial Services	Belgium	0.47**	(0.22)
MWB Fairtrade Wphdlsbank	D:MWB	Financial Services	Germany	0.34**	(0.15)
Deutsche Boerse	D:DB1	Financial Services	Germany	0.30***	(0.11)
Legal and General	LGEN	Life Insurance	United Kingdom	0.71**	(0.33)
Aviva	AV.	Life Insurance	United Kingdom	0.64*	(0.39)
FBD Holdings	IE:EG7	Nonlife Insurance	Ireland	0.88*	(0.52)
Swiss Re	S:SREN	Nonlife Insurance	Switzerland	0.70*	(0.36)
AXA	F:MIDI	Nonlife Insurance	France	0.70**	(0.34)
Sampo 'A'	M:SAMA	Nonlife Insurance	Finland	0.59*	(0.32)
Beazley	BEZ	Nonlife Insurance	United Kingdom	0.32*	(0.16)
Boot (Henry)	BOOT	REIS	United Kingdom	1.71***	(0.65)
JM	W:JMBF	REIS	Sweden	1.36**	(0.65)
Nexity	F:NXI	REIS	France	0.92*	(0.54)
Grainger	GRI	REIS	United Kingdom	0.72**	(0.31)
Echo Investment	PO:ECH	REIS	Poland	0.70**	(0.35)
Fabege	W:FABG	REIS	Sweden	0.30*	(0.18)
Unite Group	UTG	REIT	United Kingdom	0.99***	(0.37)
Unibail Rodamco We Stapled Units	H:UBL	REIT	France	0.97**	(0.48)
Eurocommercial Properties	H:ECMP	REIT	Netherlands	0.81*	(0.47)
British Land	BLND	REIT	United Kingdom	0.61**	(0.26)
Land Securities Group	LAND	REIT	United Kingdom	0.57**	(0.29)

Table 7

Physical risk exposures.

This table presents the Top 30 institutions with large and significant exposures to VMS_t, our physical risk factor. Heteroskedasticity-robust standard errors are reported in parentheses. ***, **, and * indicate significance at the 1%, 5% and 10% levels, respectively. The Code corresponds to the Datastream symbol.

Financial institutions	Code	Sector	Country	$\hat{\beta}_{VMS}$	
Sandnes Sparebank	N:SADG	Banks	Norway	2.17**	(1.08)
Sparebank 1 Nord-Norge	N:NONG	Banks	Norway	1.01*	(0.54)
Sparebanken More	N:MORG	Banks	Norway	0.41**	(0.16)
Banque Cantonale du Jura	S:BCJ	Banks	Switzerland	0.23*	(0.12)
Aurskog Sparebank	N:AURG	Banks	Norway	0.14*	(0.08)
Saint Galler Kantonalbank	S:SGKN	Banks	Switzerland	0.13*	(0.07)
Sparebank 1 Ringerike Hadeland	N:RING	Banks	Norway	-0.03**	(0.02)
Alandsbanken A	M:ALB	Banks	Finland	-0.13*	(0.08)
Berner Kantonalbank	S:BEKN	Banks	Switzerland	-0.19*	(0.11)
Invalda Invl	LT:INL	Financial Services	Lithuania	5.78**	(2.42)
Synergon Holding	BL:SYN	Financial Services	Bulgaria	3.41***	(1.31)
Kinnevik B	W:KIVB	Financial Services	Sweden	1.08*	(0.61)
Gimv	B:GIM	Financial Services	Belgium	0.73*	(0.42)
Swissquote 'R'	S:SQN	Financial Services	Switzerland	0.65**	(0.30)
Capman 'B'	M:CAP	Financial Services	Finland	0.15**	(0.06)
Bourse Direct	F:BOUS	Financial Services	France	0.14*	(0.08)
Traction B	W:TRAB	Financial Services	Sweden	0.12**	(0.02)
Ackermans and Van Haaren	B:ACK	Financial Services	Belgium	-0.03*	(0.02)
Rothschild and Company	F:ROTH	Financial Services	France	-0.42**	(0.19)
Holding Varna A	BL:HOD	Financial Services	Bulgaria	-0.51*	(0.31)
Dic Asset	D:DIC	REIS	Germany	3.00*	(1.64)
JM	W:JMBF	REIS	Sweden	2.46**	(1.23)
Tag Immobilien	D:TEG	REIS	Germany	0.99*	(0.53)
Wallenstam 'B'	W:WBYF	REIS	Sweden	0.74***	(0.29)
Castellum	W:CAST	REIS	Sweden	0.64*	(0.39)
Fastighets Balder B	W:BALB	REIS	Sweden	0.08**	(0.03)
Fast Partner A	W:FAST	REIS	Sweden	-0.04**	(0.02)
PSP Swiss Property AG	S:PSPN	REIS	Switzerland	-0.07**	(0.03)
Sagax	W:SAGA	REIS	Sweden	-0.23***	(0.08)

Table 8

Determinants of systemic risk – time series dimension

This table presents the determinants of systemic risk. Panel A presents the time-series analysis, as described in Equation (10). We use $\widehat{\Omega}_1$, the systemic risk measures derived from the first principal component defined in Equation (2), as the dependent variable. The independent variables are the $\Delta\widehat{VaR}$ of the 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. Note that a positive coefficient always indicates that a degradation in the indicator is associated with an increase in systemic risk.

Panel A: First set of factors

VARIABLES	(1) $\widehat{\Omega}_1$	(2) $\widehat{\Omega}_1$	(3) $\widehat{\Omega}_1$	(4) $\widehat{\Omega}_1$
BMG	1.392**	0.898*	1.370*	0.954**
	(0.545)	(0.486)	(0.746)	(0.461)
VMS	-0.063	-1.237	1.077	-0.843
	(1.755)	(1.850)	(1.570)	(1.402)
MKT	3.272***	3.178***		1.938***
	(0.373)	(0.423)		(0.460)
SMB	11.396***	11.202***		5.353***
	(3.356)	(3.253)		(1.892)
HML	6.118***	6.014***		2.179*
	(1.603)	(1.822)		(1.171)
RMW		-0.988		3.290
		(3.388)		(2.468)
CMA		0.325		0.135
		(0.552)		(0.456)
WML		0.623***		0.461***
		(0.231)		(0.174)
ML			6.273	-0.196
			(8.770)	(8.066)
DP			7.073***	2.370***
			(0.941)	(0.902)
YC			-0.148	0.487
			(0.512)	(0.636)
NS			3.469***	1.614
			(0.958)	(1.113)
RR			-1.438**	-0.456
			(0.665)	(0.429)
ES			1.670***	1.191***
			(0.166)	(0.182)
Constant	-0.057	-0.062	-0.059	-0.053
	(0.305)	(0.296)	(0.281)	(0.229)
Observations	207	207	207	207
R-squared	0.820	0.829	0.832	0.900
Adjusted R-squared	0.816	0.822	0.825	0.893

Panel B: Alternative set of factors

VARIABLES	(1) $\widehat{\Omega}_1$	(2) $\widehat{\Omega}_1$	(3) $\widehat{\Omega}_1$	(4) $\widehat{\Omega}_1$
BMG	2.146**	2.479***	2.005**	2.207**
	(1.020)	(0.934)	(0.951)	(0.858)
VMS	-0.930	0.047	2.935	1.207
	(1.920)	(1.700)	(1.873)	(1.206)
MKT	2.722***	2.720***		1.762***
	(0.292)	(0.301)		(0.366)
ME	3.982	2.622		1.546
	(2.693)	(2.695)		(1.636)
IA	-5.630***	-3.437*		-0.342
	(2.032)	(1.835)		(1.377)
ROE	-1.271	-0.771		-0.230
	(0.926)	(0.645)		(0.564)
EG	10.946***	8.041***		3.978***
	(1.956)	(1.453)		(1.339)
WML	-0.004	-0.024		-0.052
	(0.067)	(0.068)		(0.056)
LIQ		1.914***		1.149***
		(0.458)		(0.296)
QMJ		-0.110		-0.160*
		(0.079)		(0.082)
ML			-9.129	-6.128
			(17.174)	(12.339)
DP			8.015***	3.216***
			(1.071)	(0.918)
YC			-0.203	0.219
			(0.422)	(0.640)
NS			3.535***	0.864
			(1.247)	(0.959)
RR			-1.238*	-0.463
			(0.720)	(0.554)
ES			1.574***	0.828***
			(0.133)	(0.171)
Constant	0.183	0.069	-0.261	-0.100
	(0.317)	(0.267)	(0.289)	(0.181)
Observations	203	203	203	203
R-squared	0.870	0.899	0.880	0.929
Adjusted R-squared	0.865	0.893	0.875	0.923

Table 9

Determinants of systemic risk – cross-section dimension

This table presents the cross-sectional analysis, as described in Equation (117). The dependent variable $\hat{X}_1$ represents the loadings of each financial institution on $\widehat{\Omega}_1$. The explicative variables are the coefficients $\hat{\beta}$ extracted from Equation (6) when we replace $\widehat{\Omega}_1$ with the VaR of each financial institution. 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) and (6).

Panel A: First set of factor loadings

VARIABLES	(1) $\hat{X}_1$	(2) $\hat{X}_1$	(3) $\hat{X}_1$	(4) $\hat{X}_1$	(5) $\hat{X}_1$	(6) $\hat{X}_1$	(7) $\hat{X}_1$	(8) $\hat{X}_1$
$\hat{\beta}_{BMG}$	0.012*** (0.003)	0.012*** (0.003)	0.007*** (0.003)	0.006** (0.003)	0.010*** (0.002)	0.011*** (0.003)	0.006* (0.003)	0.007*** (0.003)
$\hat{\beta}_{VMS}$	-0.001 (0.001)	-0.0001 (0.001)	0.001 (0.001)	0.001 (0.001)	-0.001 (0.002)	-0.001 (0.002)	0.002 (0.001)	0.001* (0.001)
$\hat{\beta}_{MKT}$	0.013*** (0.004)	0.011** (0.004)		0.025*** (0.004)	0.010 (0.012)	0.008 (0.015)		0.020*** (0.003)
$\hat{\beta}_{SMB}$	0.004*** (0.001)	0.003*** (0.001)		0.003*** (0.001)	0.003*** (0.001)	0.003*** (0.002)		0.004*** (0.001)
$\hat{\beta}_{HML}$	0.004*** (0.001)	0.005*** (0.002)		0.007*** (0.002)	0.002 (0.002)	0.004 (0.005)		0.005 (0.003)
$\hat{\beta}_{RMW}$		0.001 (0.001)		0.001 (0.001)		0.001 (0.004)		0.001 (0.001)
$\hat{\beta}_{CMA}$		0.004 (0.003)		0.005*** (0.002)		0.004 (0.011)		0.005 (0.004)
$\hat{\beta}_{WML}$		0.028*** (0.009)		0.009 (0.006)		0.016 (0.010)		0.004 (0.014)
$\hat{\beta}_{RR}$			0.003 (0.002)	-0.006** (0.003)			-0.001 (0.002)	-0.009** (0.004)
$\hat{\beta}_{ML}$			0.0002** (0.0001)	0.0005*** (0.0001)			0.0001 (0.0001)	0.0003** (0.0002)
$\hat{\beta}_{DP}$			0.003*** (0.001)	0.007*** (0.001)			0.005*** (0.001)	0.007*** (0.002)
$\hat{\beta}_{YC}$			0.0002 (0.002)	-0.002 (0.002)			0.0005 (0.002)	-0.002 (0.003)
$\hat{\beta}_{NS}$			0.003*** (0.001)	-0.003*** (0.001)			0.001*** (0.0003)	-0.004*** (0.001)
$\hat{\beta}_{ES}$			0.072*** (0.008)	0.053*** (0.007)			0.063*** (0.015)	0.051*** (0.015)
Constant	0.025*** (0.003)	0.023*** (0.003)	0.022*** (0.002)	0.013*** (0.003)				
Observations	371	371	371	371	371	371	371	371
R-squared	0.145	0.174	0.255	0.377	0.309	0.321	0.406	0.478
Adjusted R-squared	0.134	0.156	0.238	0.353	0.239	0.245	0.340	0.409
Country Fixed Effects	No	No	No	No	Yes	Yes	Yes	Yes
Industry Fixed Effects	No	No	No	No	Yes	Yes	Yes	Yes

Panel B: Alternative set of factor loadings

VARIABLES	(1) $\hat{X}_1$	(2) $\hat{X}_1$	(3) $\hat{X}_1$	(4) $\hat{X}_1$	(5) $\hat{X}_1$	(6) $\hat{X}_1$	(7) $\hat{X}_1$	(8) $\hat{X}_1$
$\hat{\beta}_{BMG}$	0.011*** (0.002)	0.010*** (0.002)	0.015*** (0.003)	0.003 (0.002)	0.009*** (0.003)	0.009*** (0.002)	0.010** (0.005)	0.004** (0.002)
$\hat{\beta}_{VMS}$	0.003** (0.001)	0.003*** (0.001)	-0.002** (0.001)	0.002* (0.001)	0.002 (0.001)	0.002* (0.001)	-0.002** (0.001)	0.002 (0.002)
$\hat{\beta}_{MKT}$	0.020*** (0.006)	0.018*** (0.004)		0.029*** (0.004)	0.015*** (0.004)	0.012*** (0.005)		0.021*** (0.004)
$\hat{\beta}_{SMB}$	0.004*** (0.001)	0.004*** (0.001)		0.005*** (0.001)	0.004*** (0.001)	0.004*** (0.001)		0.004*** (0.001)
$\hat{\beta}_{IA}$	0.001 (0.001)	0.0005 (0.001)		0.0005 (0.001)	0.001 (0.001)	0.001 (0.001)		0.001 (0.001)
$\hat{\beta}_{ROE}$	0.012*** (0.003)	0.013*** (0.003)		0.012*** (0.003)	0.015*** (0.004)	0.016*** (0.004)		0.015*** (0.004)
$\hat{\beta}_{EG}$	0.008*** (0.001)	0.008*** (0.001)		0.008*** (0.001)	0.008*** (0.002)	0.008*** (0.001)		0.008*** (0.002)
$\hat{\beta}_{WML}$	-0.014 (0.016)	-0.017 (0.017)		-0.050*** (0.017)	0.001 (0.013)	-0.004 (0.022)		-0.041* (0.023)
$\hat{\beta}_{LIQ}$		0.009 (0.015)		0.040** (0.016)		0.016* (0.009)		0.039** (0.015)
$\hat{\beta}_{QMJ}$		0.009** (0.004)		0.014*** (0.004)		0.009** (0.005)		0.013** (0.006)
$\hat{\beta}_{RR}$			-0.055 (0.034)	-0.087*** (0.024)			-0.027* (0.016)	-0.064 (0.044)
$\hat{\beta}_{ML}$			-0.002 (0.003)	0.001 (0.002)			-0.003*** (0.001)	-0.002 (0.004)
$\hat{\beta}_{DP}$			-0.0003** (0.0001)	0.0002* (0.0001)			-0.0004*** (0.0001)	0.0001 (0.0001)
$\hat{\beta}_{YC}$			0.005*** (0.001)	0.007*** (0.001)			0.007*** (0.001)	0.008*** (0.002)
$\hat{\beta}_{NS}$			-0.0002 (0.001)	-0.003** (0.001)			-0.001 (0.001)	-0.002 (0.002)
$\hat{\beta}_{ES}$			-0.0003 (0.002)	-0.005** (0.002)			0.001 (0.002)	-0.003 (0.002)
Constant	0.018*** (0.003)	0.017*** (0.003)	0.028*** (0.003)	0.011*** (0.003)				
Observations	371	371	371	371	371	371	371	371
R-squared	0.292	0.300	0.114	0.420	0.408	0.416	0.320	0.492
Adjusted R-squared	0.276	0.281	0.095	0.375	0.342	0.348	0.245	0.422
Country Fixed Effects	No	No	No	No	Yes	Yes	Yes	Yes
Industry Fixed Effects	No	No	No	No	Yes	Yes	Yes	Yes

Table 10

Tail transition risk and characteristics of financial institutions.

This table presents the characteristics associated with financial institutions' exposures to climate transition risks, $\hat{\beta}_{BMG}$, estimated from Equation (6) by replacing $\widehat{\Omega}_1$ with the VaR of each financial institution. In columns (1) and (2), $\hat{\beta}_{BMG}$ is estimated statically 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. Regression (3) uses country, industry, and year fixed effects. Regressions (4) to (8) use institution and year fixed effects. Appendix B presents variable definitions. ***, **, and * indicate significance at the 1%, 5% and 10% levels, respectively.

VARIABLES	(1) $\hat{\beta}_{BMG_{avg}}$	(2) $\hat{\beta}_{BMG_{avg}}$	(3) $\hat{\beta}_{BMG_{avg}}$	(4) $\hat{\beta}_{BMG_t}$	(5) $\hat{\beta}_{BMG_t}$	(6) $\hat{\beta}_{BMG_t}$	(7) $\hat{\beta}_{BMG_t}$	(8) $\hat{\beta}_{BMG_t}$
Beta (t-1)	0.0439***	0.0234**	-0.00373	-0.300	-0.431*	-0.439**	-0.0931	-0.0921
	(0.0113)	(0.0112)	(0.0716)	(0.205)	(0.226)	(0.189)	(0.0973)	(0.0846)
LogMarketValue (t-1)	0.0236***	0.0254***	0.0746***	0.200	-0.0532	0.0269	0.0312	-0.0201
	(0.00265)	(0.00274)	(0.0161)	(0.175)	(0.185)	(0.211)	(0.0748)	(0.0645)
Cash (t-1)	-0.259***	-0.229***	-0.194	0.528	0.0251	-0.409	-0.184	0.125
	(0.0566)	(0.0629)	(0.238)	(0.762)	(1.095)	(0.774)	(0.334)	(0.343)
NetIncome (t-1)	0.252***	0.155*	-0.178	-0.928	-1.523	-0.471	-0.239	0.110
	(0.0885)	(0.0884)	(0.249)	(0.590)	(0.943)	(0.829)	(0.261)	(0.223)
MtoB (t-1)	0.00620	0.00268	-0.0432**	-0.0266	0.378**	0.251	-0.0331	-0.0576
	(0.00449)	(0.00443)	(0.0203)	(0.0930)	(0.152)	(0.172)	(0.0386)	(0.0500)
LowScope3intensity (t-1)				-0.118*				
				(0.0639)				
VerifiedScope3 (t-1)					-0.297*			
					(0.153)			
ReductionTargetReached (t-1)						-0.137**		
						(0.0678)		
Board LT incentives (t-1)							-0.0723*	
							(0.0412)	
Institutional ownership (t-1)								-0.363***
								(0.114)
Constant	-0.108***	-0.251***	-0.248	-0.693	-0.693	0.669	0.235	0.660
	(0.0170)	(0.0784)	(0.201)	(1.421)	(1.421)	(1.695)	(0.478)	(0.418)
Observations	5,992	5,992	3,245	925	715	699	3,245	2,222
R-squared	0.036	0.161	0.134	0.652	0.631	0.716	0.541	0.706
Adjusted R-squared	0.036	0.157	0.122	0.570	0.575	0.645	0.481	0.649
Country Fixed Effects	No	Yes	Yes					
Industry Fixed Effects	No	Yes	Yes					
Institution Fixed Effects	No	No	No	Yes	Yes	Yes	Yes	Yes
Year Fixed Effects	No	No	Yes	Yes	Yes	Yes	Yes	Yes

Table 11

Tail physical risk and characteristics of financial institutions.

This table presents the characteristics associated with financial institutions' exposures to physical climate risk, $\hat{\beta}_{VMS}$, estimated from Equation (6). 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 variable definitions. ***, **, and * indicate significance at the 1%, 5% and 10% levels, respectively.

VARIABLES	(1) $\hat{\beta}_{VMS_{avg}}$	(2) $\hat{\beta}_{VMS_{avg}}$	(3) $\hat{\beta}_{VMS_t}$	(4) $\hat{\beta}_{VMS_t}$	(5) $\hat{\beta}_{VMS_t}$
Beta (t-1)	0.299*** (0.0538)	0.327*** (0.0496)	0.433* (0.224)	0.0898 (0.319)	-0.387 (0.293)
LogMarketValue (t-1)	-0.0934*** (0.0106)	-0.0544*** (0.0109)	-0.0527 (0.0424)	-0.434** (0.186)	-0.434* (0.224)
Cash (t-1)	-0.334* (0.201)	0.521** (0.226)	-0.0367 (0.588)	0.0485 (0.519)	0.688 (0.545)
NetIncome (t-1)	0.265 (0.319)	0.439 (0.323)	0.211 (0.768)	0.396 (0.675)	-0.285 (0.824)
MtoB (t-1)	-0.0513*** (0.0189)	-0.0310* (0.0178)	-0.0160 (0.0787)	0.113 (0.0964)	0.243** (0.102)
Board LT incentives (t-1)				-0.0175 (0.159)	
Institutional ownership (t-1)					-0.0908 (0.324)
Constant	0.310*** (0.0627)	1.665*** (0.226)	0.595 (0.618)	2.917** (1.280)	2.996* (1.533)
Observations	5,992	5,992	3,245	3,245	2,222
R-squared	0.020	0.217	0.139	0.504	0.644
Adjusted R-squared	0.019	0.213	0.127	0.439	0.575
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 12

Tail climate risk and adaptation measures.

This table presents estimates of the effect of tail climate risk 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. Columns (1), (2), (3), (4) and (5) use IntegratedStrategy, DiscussClimateRisk, LogCarbonOffsets, TradingAllowances, and PolicyEngagement as dependent variables, respectively. Regressions (1), (2), (4), and (5) use a probit model. Regression (3) 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), (3), (4) and (5) use ResourceScore, EnvironmentalTeam, EnvironmentalProducts, SupplierClimateEngagement, and ClimateScenarioAnalysis as dependent variables, respectively. Regression (1) uses an OLS model. Regressions (2), (3), (4), and (5) use a probit model. All regressions use country-year and sector-year fixed effects. Appendix B presents variable definitions. Standard errors are clustered at the financial institution level and t-values are reported in parentheses. ***, **, and * indicate significance at the 1%, 5% and 10% levels, respectively.

Panel A: Transition risk

	(1)	(2)	(3)	(4)	(5)
VARIABLES	IntegratedStrategy	DiscussClimateRisk	Environmental Disclosure Score	LogCarbonOffsets	PolicyEngagement
$\hat{\beta}_{BMG}$ (t-1)	0.246***	0.323***	-0.0261**	0.413*	-0.397**
	(0.0940)	(0.111)	(0.0127)	(0.245)	(0.201)
Beta (t-1)	0.340	-0.114	-0.0274	0.884	0.884**
	(0.245)	(0.216)	(0.0240)	(0.713)	(0.350)
LogMarketValue (t-1)	0.336***	0.314***	0.0202*	0.832**	0.447***
	(0.0998)	(0.0794)	(0.0109)	(0.359)	(0.139)
Cash (t-1)	1.303	0.137	-0.0440	1.931	6.126***
	(1.017)	(1.171)	(0.276)	(1.757)	(1.939)
NetIncome (t-1)	-3.417*	-4.162***	-0.226	2.864	0.122
	(1.779)	(1.503)	(0.209)	(2.693)	(2.413)
MtoB (t-1)	-0.0828	-0.104	0.00823	-0.0558	-0.260**
	(0.0969)	(0.0777)	(0.0162)	(0.167)	(0.117)
ESG Disclosure Score (t-1)	0.00332	0.0457***	0.00466***		
	(0.0117)	(0.0121)	(0.00166)		
Constant	-2.297***	-1.067	0.183*	-4.796	-1.397
	(0.673)	(0.688)	(0.103)	(3.836)	(1.114)
Observations	1,136	1,292	978	335	812
R-squared			0.709	0.618	
Adjusted R-squared			0.635	0.339	
Country-Year Fixed Effects	Yes	Yes	Yes	Yes	Yes
Industry-Year Fixed Effects	Yes	Yes	Yes	Yes	Yes

Panel B: Physical risk

VARIABLES	(1) ResourceScore	(2) EnvironmentalTeam	(3) EnvironmentalProducts	(4) ClimateScenario Analysis	(5) SupplierClimate Engagement
$\hat{\beta}_{VMS}$ (t-1)	1.131*	0.123***	0.0979***	0.0958*	0.533***
	(0.615)	(0.0427)	(0.0349)	(0.0502)	(0.174)
Beta (t-1)	10.29***	0.309	0.249	0.0564	0.0579
	(3.302)	(0.235)	(0.238)	(0.325)	(0.514)
LogMarketValue (t-1)	11.59***	0.575***	0.710***	0.551***	1.401***
	(0.967)	(0.0827)	(0.0848)	(0.102)	(0.285)
Cash (t-1)	31.04	0.691	5.160***	1.766	8.711**
	(19.66)	(1.292)	(1.386)	(1.669)	(4.334)
NetIncome (t-1)	-62.26**	-1.697	-2.942*	-2.109	-3.323
	(25.08)	(1.492)	(1.748)	(2.612)	(3.532)
MtoB (t-1)	-3.402**	-0.134	-0.192**	-0.0477	-0.129
	(1.472)	(0.0833)	(0.0898)	(0.0864)	(0.142)
Constant	-70.37***	-3.704***	-5.524***	-4.075***	-6.687***
	(10.55)	(0.660)	(0.748)	(0.800)	(2.005)
Observations	1,273	1,256	1,341	757	353
R-squared	0.566				
Adjusted R-squared	0.482				
Country-Year Fixed Effects	Yes	Yes	Yes	Yes	Yes
Industry-Year Fixed Effects	Yes	Yes	Yes	Yes	Yes