Systemic Climate Risk

Abstract

This paper proposes a new framework to study systemic climate risks in the financial sector. Using market-based measures of physical and transition climate risks, we identify which European financial institutions are the most vulnerable to climate risks and test whether climate risks can generate tail dependence among financial institutions. We show that, unlike physical risk, transition risk significantly influences systemic risk. The exposure to transition risk appears lower for institutions with cleaner investment and lending portfolios. Besides, the financial institutions most exposed to transition risk tend to engage more in carbon disclosure.

JEL Classification: G10, G20, G32, Q54

Keywords: Climate risk, climate change, ESG, financial stability, interconnectedness, tail dependence, systemic risk, carbon disclosure

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 individual 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 risk."

This article proposes a new analytical framework based on environmental and stock market data to empirically 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 existing papers focus on individual vulnerabilities (e.g., Alessi et al., 2021; Jung et al., 2021; Ojea Ferreiro et al., 2022), our framework also test whether climate risks can exacerbate tail dependence 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 climate 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.

We proceed in several steps. *First*, for the purpose of our study, we design a new systemic risk measure, related to the methods suggested by Adams et al. (2014), Adrian and Brunnermeier (2016), and Kelly and Jiang (2014). Specifically, using a GARCH model, we estimate time-varying Value-at-Risk (VaR) measures from the stock returns of financial institutions. Equity returns are intended to be informative about the risks of financial institutions and may reflect information more quickly than accounting variables. 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 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. Using a large sample of dead and alive stocks (excluding financial sector companies), we build two long-short factor mimicking portfolios,

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[1] See also here.

respectively based on carbon emission intensity and physical risk scores. 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 the best of our knowledge, 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 factors are related to stock return comovements and extend their approach to tail risks. In addition, we propose a robustness test that exploits cross-sectional information on individual climate risk exposures and individual loadings on systemic risk. More precisely, we start by running a time-series regression of the variations in systemic risk on climate risk factors and a list of control variables representing other potential determinants of systemic risk. This step allows us to verify whether a rise in climate risks is associated with an overall increase in downside risk within the financial sector. We then perform a cross-sectional regression of financial institutions' contributions to systemic risk on financial institutions' exposures to climate risks. We control for other risk exposures, include fixed effects for country and financial industry, and compute clustered standard errors. This step examines 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 measure, that incorporates extreme climate risks as potential stress factors for financial institutions.

Fourth, we investigate the characteristics of the financial institutions that are correlated with individual climate risk exposures. Understanding these characteristics is essential for regulators and financial practitioners to undertake actions to mitigate systemic climate risks. Specifically, we examine the effect of various financial characteristics, as well as environmental and governance characteristics, on the level of climate risk exposure. We then analyze how financial institutions adapt to these climate risks, with a focus on carbon disclosure policies.

Overall, our framework provides a tool to evaluate the current level of vulnerability of financial institutions to climate risks and dynamically monitor whether the effect of climate risks on financial stability is becoming a growing threat for investors. Our approach can also help financial institutions and supervisors identify levers to mitigate systemic climate risks. Finally, our findings can be exploited as inputs in stress-testing exercises (e.g., Dietz et al., 2016; Battiston et al., 2017; Roncoroni et al., 2021; Vermeulen et al., 2018) and should be considered complementary to research on the development of climate scenarios and assumptions about the future impact of climate risks on asset prices, which is subject to considerable uncertainty (Barnett et al., 2020).

Our empirical analysis is based on a sample of European stocks, spanning from 2005 to 2022 and extracted from Refinitiv Datastream. For financial institutions, we focus on 332 stocks with a market capitalization above €100 million in 2022. Our results indicate that transition risks significantly affect the VaR of financial institutions and, more importantly, can exacerbate tail dependence within the financial sector. By contrast, we do not find evidence of such an effect 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.

Looking at the characteristics of institutions correlated 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 from Carbone 4, we also show that institutions with cleaner investment and lending portfolios are less exposed to transition risks. Lastly, our analysis indicates that transition risk exposure is a significant determinant of carbon disclosure decisions among financial institutions.

Our study is linked to the literature on the influence of climate risks on financial markets. Many papers find premiums associated to climate risks in equity markets (e.g., Ardia et al., 2020; Bolton and Kacperczyk, 2021; Choi et al., 2020; Görgen et al., 2020), real estates (e.g., Bernstein et al., 2019; Baldauf et al., 2020; Murfin and Spiegel, 2020) or bond markets (e.g., Flammer, 2021; Zerbib, 2019). Despite these premiums, other papers point out that climate risks remain underestimated by market participants (e.g., Hong et al., 2019; Alok et al., 2020; Kruttli et al., 2020).[2] Andersson et al. (2016) and Engle et al. (2020) suggest approaches to dynamically hedge climate risks using climate news. Besides, several papers examine how financial institutions adjust their operations as a consequence of climate events (e.g., Manconi et al., 2016; Schüwer et al., 2019; Ge and Weisbach, 2021; Massa and Zhang, 2021). We contribute to this literature by assessing whether climate risks can affect the tail risk of financial institutions, highlighting how financial institutions adapt to these risks, and identifying the levers financial institutions might have to reduce their exposure to climate risks. To the best of our knowledge, only Li et al. (2020) and Sautner et al. (2020) propose an institution-level measure of climate risk and investigate which characteristics correlate with this measure, and we are the first to adopt such an approach using a market-based measure of tail climate risks.

[2] All these articles should be conceptually distinguished from studies assessing how considerations on Corporate Social Responsibility (CSR) affect asset returns, for example Lins et al. (2017), 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 various Environmental, Social, and Governance (ESG) and climatic dimensions on extreme returns. Lins et al. (2017) show that firms with good ESG 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 option markets. Several articles examine how certain individual ESG characteristics may help reduce systemic risk measures, such as $\Delta CoVaR$ and $SRISK$ (Anginer et al., 2018; Scholtens and van't Klooster, 2019; Cerqueti et al., 2021; Kleymenova and Tuna, 2021; Aevoae et al., 2022). Jung et al. (2021) develop a climate systematic risk measure (CRISK), derived from the SRISK indicator (Brownlees and Engle, 2017), which focuses on banks' exposure to fossil fuels. Related methodologies to assess individual climate risk exposures 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 derived from Adrian and Brunnermeier's (2016) work. Third, our framework places a central focus on tail dependence among financial institutions, a key aspect of systemic risk, allowing us to capture the potential second-round effects of climate risks. Overall, compared to previous studies, we provide a more comprehensive study on the quantification and financial stability implications of climate risks for financial institutions.

We also contribute to the literature on the determinants and consequences of nonfinancial reporting. On the one hand, many papers investigate the determinants of voluntary nonfinancial disclosure. Firm size, regulations regarding disclosure, profitability, leverage, and industry affiliation are significant predictors of the choice of disclosing nonfinancial information (e.g., Cormier and Magnan, 1999; Brammer and Pavelin, 2006; Dhaliwal et al., 2011). Ilhan et al. (2021a) further show that institutional ownership increases the likelihood of voluntarily disclosing non-financial information, while Cormier and Magnan (1999) find that concentrated ownership decreases it. The characteristics of CEOs, shareholder resolutions and the threat of new regulations also influence nonfinancial disclosure (e.g., Haniffa and Cooke, 2005; Reid and Toffel, 2009; Lewis et al., 2014). On the other hand, several papers study the impact of voluntary or mandatory nonfinancial disclosure on various outcomes such as firm value (e.g., Matsumura et al., 2014; Plumlee et al., 2015; Griffin et al., 2017; Grewal et al. 2019), cost of equity (e.g., Dhaliwal et al., 2011), analyst forecast accuracy (e.g., Dhaliwal et al., 2012), or subsequent nonfinancial performance (e.g., Christensen et al., 2017; Kim et al., 2022). We contribute to this literature by showing that exposure to climate transition risks significantly increases the propensity of financial institutions to disclose their carbon emissions.

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 new measure of systemic risk among financial institutions based on common variations in the VaR of financial institutions. It relates to Adrian et al. (2016) CoVaR measure insofar as it examines how one institution's tail risk evolves conditional on the others. Our setup also shares similarities with Adams et al. (2014), as we first estimate the VaR (see Section 2.2) of each financial institution and then investigate their comovements. We extract common variations in VaR based on a principal component analysis. We argue that this approach is better suited to relatively large samples than the vector autoregressive models proposed by Adams et al. (2014). 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. 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. However, unlike their approach, we can use our setup to derive time-varying individual measures of tail risk.

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

$$\Xi = [diag(\Sigma)]^{-1/2} \Sigma \, [diag(\Sigma)]^{-1/2} \tag{1}$$

with $\Sigma = N^{-1}T^{-1}\overline{\Delta VaR}'\overline{\Delta VaR}$, N being the number of financial institutions, T the length of the period, and $\overline{\Delta VaR}$ a matrix of de-meaned VaR measures, in first difference to ensure stationarity. 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 ξ: $[\xi_1, \dots, \xi_j]$ 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 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.

Our two-pass regression procedure to test whether climate risks can generate tail dependence among financial institutions consists of the following steps. We start by running a time-series OLS regression of $\widehat{\Omega}_1$ onto a set of climate risk factors, BMG and VMS, and control risk factors f:

$$\widehat{\Omega}_{1,t} = \alpha + \beta_{BMG} BMG_t + \beta_{VMS} VMS_t + \sum_{i=3}^{I} \beta_{f_i} f_{i,t} + \varepsilon_t, \quad i,i,d.\ \varepsilon \sim \mathcal{N}(0,1) \tag{4}$$

where BMG_t and VMS_t are the transition and physical climate risk factors, described in Section 2.3, and f is a T × (I-3) matrix containing a list of control variables. We use a modified version of Fama and French (2015) factors and other variables capturing the degree of risk aversion, interbank market liquidity, default premium, and the state of the economic activity. This regression estimates the effect of an increase in climate risks on simultaneous changes in the downside risk of financial institutions.

By successively replacing $\widehat{\Omega}_1$ in Equation (4) by $\Delta\widehat{VaR}_j$, the VaR of each financial institution j, where $j \in [1\colon N]$, we obtain $\hat{\beta}$, a $N \times I$ matrix of the sensitivity of the VaR of each financial institution to our climate extreme risk factors as well as other control variables mentioned above. This measure is akin to a "Climate" Exposure CoVaR indicator, as it analyzes how climate risks contribute to each financial institution's stress.

We then perform a cross-sectional OLS regression of $\hat{X}_1$, the loadings of each financial institutions j to $\widehat{\Omega}_1$, onto $\hat{\beta}$:

$$\hat{X}_{1,j} = \alpha + \gamma_{BMG} \hat{\beta}_{BMG,j} + \gamma_{VMS} \hat{\beta}_{VMS,j} + \sum_{i=3}^{I} \gamma_{f_i} \hat{\beta}_{f_{i,j}} + \varepsilon_j, \quad i,i,d.\ \varepsilon \sim \mathcal{N}(0,1) \tag{5}$$

This second regression tests whether the financial institutions most exposed to climate risks have stronger tail dependence with the rest of the financial sector.

We consider that climate risks exacerbate tail dependence among financial institutions if the respective coefficients $\hat{\beta}_{BMG,j}$, $\hat{\beta}_{VMS,j}$, $\hat{\gamma}_{BMG}$, $\hat{\gamma}_{VMS}$ are both positive and significant. We estimate standard errors based on Newey and West (1987) for time-series regressions and White (1980) for cross-sectional regressions.

2.2. 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 dependences. 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). We argue that measuring comovements among tail risk indicators is better suited to capture systemic risk than relying on return comovements. Besides, Table 1 shows that the largest interconnections between financial institutions are different whether we use the comovements among returns or VaR to identify them.

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 equals to 95%, the 1-month θ-VaR shows the negative return that will not be exceeded within this month with a 95% probability:

$$prob[return_t < -VaR_t | \Omega_t] = \theta \tag{6}$$

VaR can be estimated dynamically based on Equation (7):

$$\widehat{VaR}_{i,t} = \hat{\mu}_{i,t} + \hat{\sigma}_{i,t|t-1} F(1-\theta)^{-1} \tag{7}$$

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 skewed normal 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 $t-1$ impact the variance at time t more strongly than positive returns (leverage effect). To reflect this effect, we apply the threshold

GARCH model of Glosten et al. (1993) presented in Equation (8). This is the simplest asymmetric GARCH specification, which seems appropriate given our relatively small sample. We confirm that the parameter γ in Equation (8) is positive for 257 financial institutions and positive and significant at the 10% level for 111 series out of 332.

$$\hat{\sigma}_{i,t}^2 = \omega + (\alpha + \gamma \mathbb{I}_{t-1})\varepsilon_{t-1}^2 + \beta \hat{\sigma}_{i,t-1}^2 \tag{8}$$

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

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

Table 2 tests the ability of our model to fit the data and capture tail risk. In Panel A, we present the Akaike, Bayes, Shibata, and Hannan Quinn information criteria for different model specification and error distribution assumptions. 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. Potential alternatives would be the exponential GARCH model of Nelson (1991) or the component GARCH of Engle and Lee (1999). 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 result 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. Overall, our results are robust to other GARCH specifications and assumptions on the error distribution.

2.3. Factor construction

The climate finance literature has suggested several approaches to building climate risk indicators. Ardia et al. (2021) 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. Brière and Ramelli (2021) construct a climate stress indicator using investor flows toward sustainable ETFs. 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 and construct two climate risk factors using a large sample of dead and alive 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). 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 Section 2.1.

In the case of transition risks, the long and short positions are determined by their carbon emission intensity.[3] We use both reported and estimated emissions, Scopes 1 & 2, divided by net sales, from Refinitiv Datastream. To mitigate correlation with existing factors (see Table 3), the transition risk factor is constructed using six value-weighted portfolios formed on market capitalization (B for "Big", S for "Small", see Equation 9), 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 based on the median value of the market capitalization and the book-to-market in our sample.

$$BMG_t = \frac{LB_t + HB_t + SB_t + BB_t}{4} - \frac{LG_t + HG_t + SG_t + BG_t}{4} \tag{9}$$

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. We only include in the portfolios the stocks for which all data 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. In contrast with BMG, the correlation between the physical climate factor and the "value" factor (HML) is naturally low (see Table 3), so we only filter portfolios based on market capitalization.

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[3] 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").

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"):

$$VMS_t = \frac{SV_t + BV_t}{2} - \frac{SS_t + BS_t}{2} \tag{10}$$

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. As a result, all portfolios are constructed from a sample of 2,237 European non-financial stocks.

2.4. Data sources

From Refinitiv Datastream, we obtain an initial list of over 21,805 active and dead European stocks (including members of the European Union, Norway, Switzerland, and the United Kingdom) for which we download a large set of financial variables in euros, such as prices (including dividends), market capitalizations, book values of equity, cash holdings, total assets, incomes, net sales, and fixed assets.[4] We compute log returns from the available price series (17,454) and apply several filters recommended by Landis and Skouras (2021) to deal with implausible returns, illiquidity, and unusually high or low volatility. First, we eliminate from our sample the series for which more than 95% of the returns have the same sign (positive or negative). Second, we discard the series for which more than 25% of the returns are equal to

[4] 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.

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%.

Based on this dataset, we select financial institutions according to the Refinitiv Datastream sector denomination (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 financial institutions in Europe with a market capitalization greater than 100 million euros as of June 2022. Our final sample consists of 332 financial institutions, including 119 banks, 10 life insurance companies, 29 non-life insurance companies, 86 financial services companies, 65 real estate investment and services firms (REIS), and 23 real estate investment trusts (REITs).

We download several financial and environmental variables for this sample of financial institutions (see the list and definitions in Appendix A). Financial variables, Scope 1 & 2 carbon emissions and variables on environmentally responsible initiatives and board member incentives are from Refinitiv Datastream. Physical risk scores are downloaded from Trucost. Finally, we use Scope 3 carbon emissions from Carbone 4, which estimates the indirect emissions of financial institutions mainly originating from their investment and loan portfolios.[5]

To construct climate risk factors, we only keep the stocks for which information on climate risks (carbon emissions or physical scores), as well as other relevant financial information (market capitalization, book-to-market, and net sales) are available. We download Fama and French (2015) and Carhart (1997) factors from Kenneth French website. The European Fama

[5] 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.

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 profile. Carhart (1997) also proposes the Winner-minus-Loser factor (WML), which captures a momentum effect. For consistency with the transformation applied for climate risk factors and financial institutions' stock returns, we focus on the tail risk of each of these factors.

Besides, we construct several market stress factors. We download the risk reversal on the USD/EUR options from Bloomberg (RR), for which a negative value implies that expectations are skewed towards a depreciation of the euro. Then, we build a series of fixed income spreads. The 3-month Euribor rate against the OIS represents interbank market liquidity (IM). The 10-year against the 2-year euro area interest rates captures 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. In the regressions, a positive coefficient associated with one of these variables indicates that a deterioration in the indicator leads to an increase in systemic risk. Additional information on data sources is available in Appendix A.

2.5. Descriptive statistics

Table 3 reports the correlation matrix between our tail climate risk factors, BMG (transition risk factor) and VMS (physical risk factor), the five factors of Fama and French (2015), the momentum factor of Carhart (1997), and several market stress factors. Overall, the correlation of climate risk factors with existing factors is low. BMG is slightly correlated with WML, CMA, and HML, at 23%, 21%, and -20%, respectively. VMS is moderately correlated with ES and MKT, at 24% and 21%, respectively. The highest correlations among risk factors are between ES and HML, ES and MKT, as well as RMW and HML, at 63%, 48%, and 47%, respectively. The correlation between BMG and VMS amounts to 8%.

In Table 4, Panels A and B report the characteristics of the factor constituents. As of 2022, the BMG factor comprises 414 brown firms and 414 green firms. We observe a high sector concentration in both the long and short portfolio allocations. For example, the personal goods industry, a low-carbon sector, is most represented in the green portfolio, while the oil and gas production industry, a very carbon-intensive sector, is 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 €19,115 million (€10,703 million) for the brown (green) portfolio, while the weighted average carbon intensity is 618% (0.28%).

As of 2022, the BMG factor comprises 421 firms that are vulnerable to physical risk and 490 firms that are deemed safe. The weighted average market capitalization amounts to €9,293 million (€1,786 million) for the vulnerable (safe) portfolio. The vulnerable (safe) portfolio has an average physical risk score of 62 (32).[6] To alleviate the effect of the size divergences, we control for market capitalization in the construction of the BMG and VMS factors (see Equation

[6] This score goes from 0 (extremely low risk) to 100 (extremely high risk). 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).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).

9).Table 5 presents the descriptive statistics of the 332 European financial institutions included in our sample. The average (median) market capitalization of our institutions is €914 million (€816 million), with an average net income to total assets ratio of 0.025 (median = 0.010), an average market-to-book of 1.291 (median = 1.004), an average beta of 0.831 (median = 0.780), and an average Scope 3 emissions (in tons) to sales (in thousand euros) of 6.907 (median = 3.512). In addition, 26.7% of our institution-year observations voluntarily disclose their Scope 1 and/or Scope 2 emissions.

3. Empirical results

3.1. Measure of systemic risk

Figure 1 represents our time-varying systemic risk indicator ($\widehat{\Omega}_1$) from February 2005 to April 2022. $\widehat{\Omega}_1$ 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. Table 1 shows that most financial institutions contribute positively to systemic risk. Among the top 30 contributors, banks are the most represented institutions (19 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 10 insurance companies are gathered in the sample based on returns, only 2 emerge when tail risks are considered.

3.2. Individual exposures of financial institutions to tail climate risks

Figure 2 plots the distribution of transition and physical risk exposures of financial institutions estimated in Equation (4). 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 exposures. The same is true for physical risk exposures but to a lesser extent.

Table 6 presents the 30 largest individual exposures to tail transition risk. Among the 30 financial institutions, 13 are from the United Kingdom. The largest exposure is Bank of Ireland with a coefficient of 3.36, meaning that if transition risk worsens by one percentage point, the VaR of Bank of Ireland will deteriorate by 3.36 percentage points. On average within this group, a one percentage point decrease in the VaR of the transition risk factor leads to a 1.51 percentage point decline in the VaR of the financial institutions. This group comprises 8 financial institutions with a market capitalization above €10 billion, including 3 life insurers (Aviva, Legal and General, Prudential), 3 non-life insurers (AXA, Sampo, Swiss Re), and 2 banks (Barclays and Lloyds Banking Group).

Table 7 reports the 30 largest exposures to tail physical risk. Among these 30 largest exposures, 8 are Norwegian institutions. The Norwegian financial services provider Aker has the largest exposure to physical risk, with an individual VaR worsening by 2.69 percentage points when physical risk deteriorates by one point. Among the 30 most vulnerable financial institutions, the mean exposure is equal to 0.86. This group only comprises 1 financial institution with a market capitalization above €10 billion (Swedbank). We also find a relative overrepresentation of REITs in the largest exposures to tail physical risk, with 4 out of the 23 REITs in our sample being among the 30 largest exposures to tail physical risk. The mean exposure of these 4 REITs is equal to 1.15. One possible explanation is that REITs tend to have more tangible assets compared to other financial institutions, and are therefore more vulnerable to asset destructions stemming from extreme climate events.

3.3. The effect of tail climate risks on systemic risk

In Table 8, we examine whether tail climate risks significantly contribute to tail dependence among financial institutions, after taking into account several factors known to be predictors of systemic risk. We start by running time-series 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, see Panel A). In column (1), we observe a positive and significant impact of transition risks on systemic risk, after controlling for MKT, SMB, and HML factors, while physical risks have no significant effect. We confirm these results when we add controls for (i) RMB, CMA, and WML (column 2), (ii) various market stress indicators (RR, ML, DP, YC, NS, ES in column 3), and all control variables together (column 4). Finally, in column 5, we include industry fixed effects and validate the previous findings. For ease of interpretation, we change the sign of some variables so that a positive coefficient always indicates that a degradation in the indicator is associated with an increase in systemic risk. We note that most of the market stress indicators are positively associated with systemic risk.

Next, we carry out a cross-sectional analysis (Panel B) 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 ($\widehat{\mathrm{X}}_1$), after controlling for the exposures to other risk factors. Again, we find positive and significant coefficients associated with the exposure to transition risks, while the exposure to physical risks does not seem to affect financial institutions' contribution to global risk. The results are robust to the inclusion of fixed effects for country and financial industry, as well as clustered standard errors. Interestingly, the sign and degree of significance of the coefficients of the time series and cross-sectional regressions are not always in line, 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 robustness of the results.

Overall, our findings indicate that transition risks significantly contribute to systemic risk, both in the time series and the cross section dimensions. On the contrary, physical risks do not appear to impact systemic risk.[7]

3.4. Individual characteristics of financial institutions and tail climate risks

In this section, we investigate which institution-level characteristics are associated with tail climate risks. We report our results in Table 9 in the case of tail transition risks. We start by regressing our measure of tail transition risks on the natural logarithm of market capitalization, net income, market-to-book, cash, equity beta, as well as country and industry fixed effects. Our results, reported in column (1), indicate that market capitalization and equity beta are positively associated with individual tail transition risk, while transition risk exposure is negatively correlated with cash levels.[8] We then augment our regressions with additional characteristics. We first investigate the impact of Scope 3 CO_2 emissions (CO_2 emissions indirectly emitted by the financial institutions, primarily through their investment and loan

[7] 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 impact our findings on physical risk.

[8] 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.

portfolios). We find that higher Scope 3 emissions intensity is positively associated with transition risk exposures (column 2). We then assess the association between transition risks and financial institutions' commitment to managing environmental issues in project financing, as proxied by being an Equator Principles signatory. Our results indicate that financial institutions managing environmental issues in project financing tend to have lower transition risk exposures (column 3). In column (4), we investigate the relationship between the long-term incentives given to board members and transition risks. We find that exposures to transition risks are significantly lower when board members have long-term incentives.[9]

In Table 10, 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, higher cash holdings, and lower equity beta (column 1). As with transition risks, physical risks tend to be lower for institutions committing to managing environmental issues in project financing (column 2) and giving long-term incentives to board members and executives (column 3).

These findings suggest that the characteristics of financial institutions exposed to tail transition risks are different from those of institutions exposed to physical risks. However, financial institutions tend to have lower exposure to both transition and physical risks when they commit to taking environmental considerations, or more broadly long-term considerations, into account.

[9] 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."*

3.5. Tail climate risks and environmental disclosure policies

According to previous results, tail transition risks influence systemic risk within the financial sector. In this section, we thus investigate whether financial institutions take action to adapt to tail climate risks. More specifically, we assess the impact, if any, of tail climate risks on carbon disclosure policies. Our results are reported in Table 11. In column (1), we start by regressing $CO2\ disclosure$, a dummy variable equal to one if the financial institution reports Scope 1 and/or Scope 2 emissions, on our measure of transition risk, after controlling for the natural logarithm of market capitalization, net income, market-to-book, cash, beta, as well as year fixed effects. All our control variables are lagged by one year to mitigate potential endogeneity issues. Then, in columns (2) and (3), we add country and industry fixed effects to control for time-invariant industry and country characteristics. Across our specifications, our findings indicate a positive and significant effect of tail transition risks on the disclosure of CO2 emissions, after controlling for various determinants of CO2 emissions disclosure. A one standard deviation increase in tail transition risks is associated with a 2.6 to 3.2 percentage point increase in the probability to disclose CO2 emissions, corresponding to a 10 to 11% increase from the mean. However, our findings could be biased by endogeneity. Omitted time-invariant institution characteristics might bias our results. In column (4), we thus recompute our transition risk measure estimated in Equation (4) on 3-year intervals. Having multiple transition risk scores per financial institution allows us to confirm the positive impact of transition risks after the inclusion of financial institution fixed effects. Another endogeneity concern is reverse causality. To mitigate this concern, we implement an instrumental variable approach, in which we instrument our 3-year transition score by the average 3-year transition score within the same sector-year group, the underlying assumption being that peer institutions' transition risk does not influence the carbon disclosure decisions of the focal firm. Our results are reported in columns (5) and (6) and indicate that a one-standard-deviation increase in transition risk increases by 6.4 percentage points the probability to disclose carbon emissions.

Overall, our results indicate that tail transition risks positively impact the propensity of financial institutions to engage in carbon disclosure.

4. Conclusion

In this paper, we develop a new framework for analyzing systemic climate risks based on environmental and stock market data. This framework aims to identify the institutions that are the most vulnerable to climate risks and assess whether climate risks can exacerbate tail risk dependence within the financial sector. We apply our approach to a sample of Europe's largest financial institutions. We find that many financial institutions are positively and significantly exposed to climate risks and show that transition climate risks can exacerbate tail dependence among financial institutions, which is a key aspect of systemic risk. By contrast, we do not find evidence of such spillovers in the case of physical climate risks.

Studying the institution-level characteristics associated with climate risks, we find that climate risk exposure is lower for financial institutions committed to environmental risk management and for those providing long-term incentives to board members. Our findings also highlight that financial institutions with cleaner investment and lending portfolios tend to be less exposed to transition risks. Finally, our results reveal that financial institutions are more prone to disclosing carbon emissions when they are more exposed to transition risks. In a nutshell, our findings suggest that managers of financial institutions have levers to reduce systemic climate risks. However, our analysis is silent on the tradeoff that might exist between the reductions in climate risk exposures and the potential costs of implementing these actions. The characteristics we find associated with climate risk might be of interest for microprudential supervision. Furthermore, our findings regarding tail dependence also suggest that financial supervisors might want to consider integrating transition risk into their macroprudential oversight.

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. We argue that this perception is critical for financial institutions because the threat that climate risks pose to financial stability depends largely on investors' repricing of financial assets. Moreover, our proposed market-based framework is more responsive than other accounting-based models and could be used to dynamically monitor the prevalence of systemic climate risks. As a result, our findings could also be used as inputs in the development of climate scenarios and assumptions about the future impact of climate risks on asset prices. Finally, the framework we design in this paper is flexible and could be applied to other countries, industries, asset types, or time periods. 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 in question are available.

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Figure 1

Time variations in systemic risk from February 2005 to April 2022.

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.

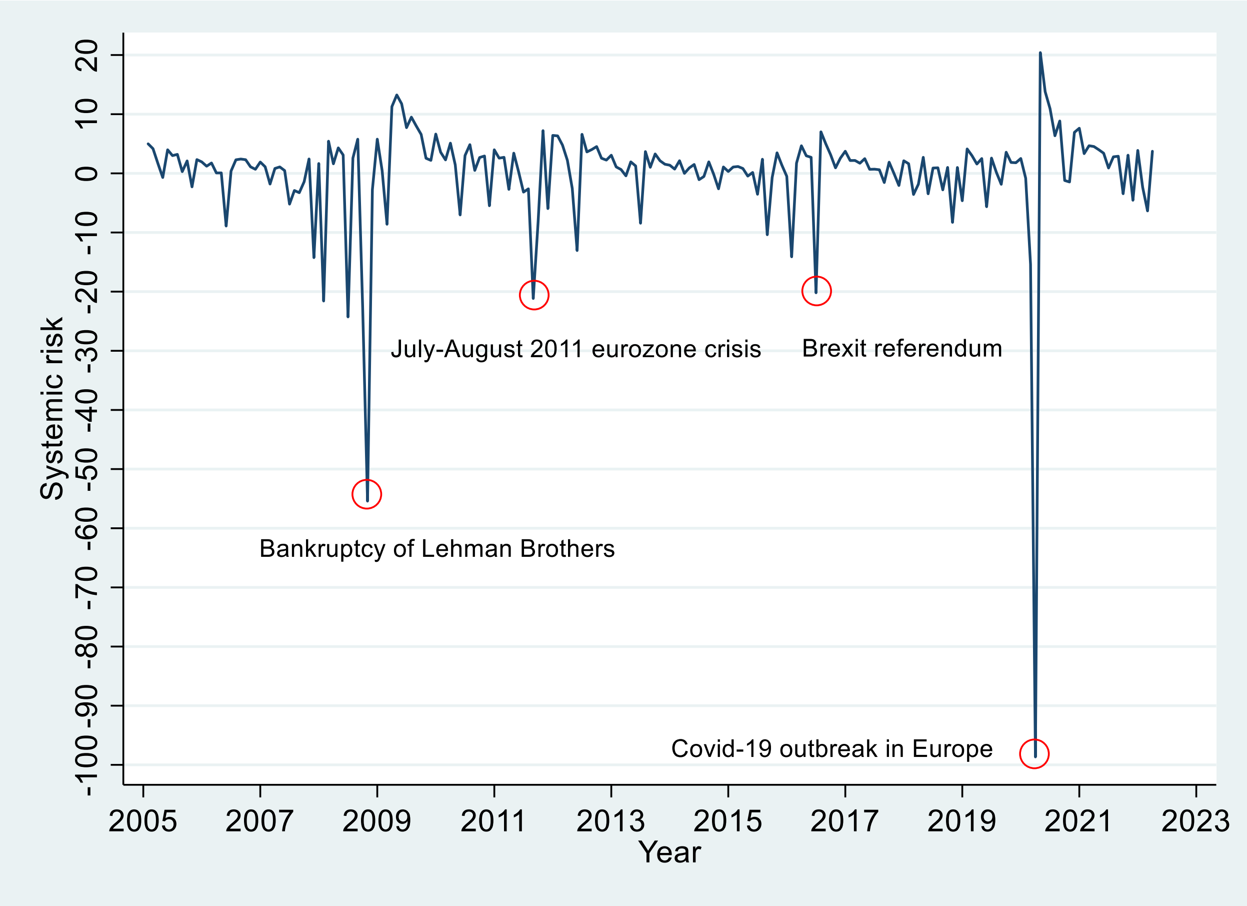

Figure 2

Distribution of climate risk exposures for 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 (4) by replacing $\widehat{\Omega}_1$ with the time variations in the VaR of financial institutions.

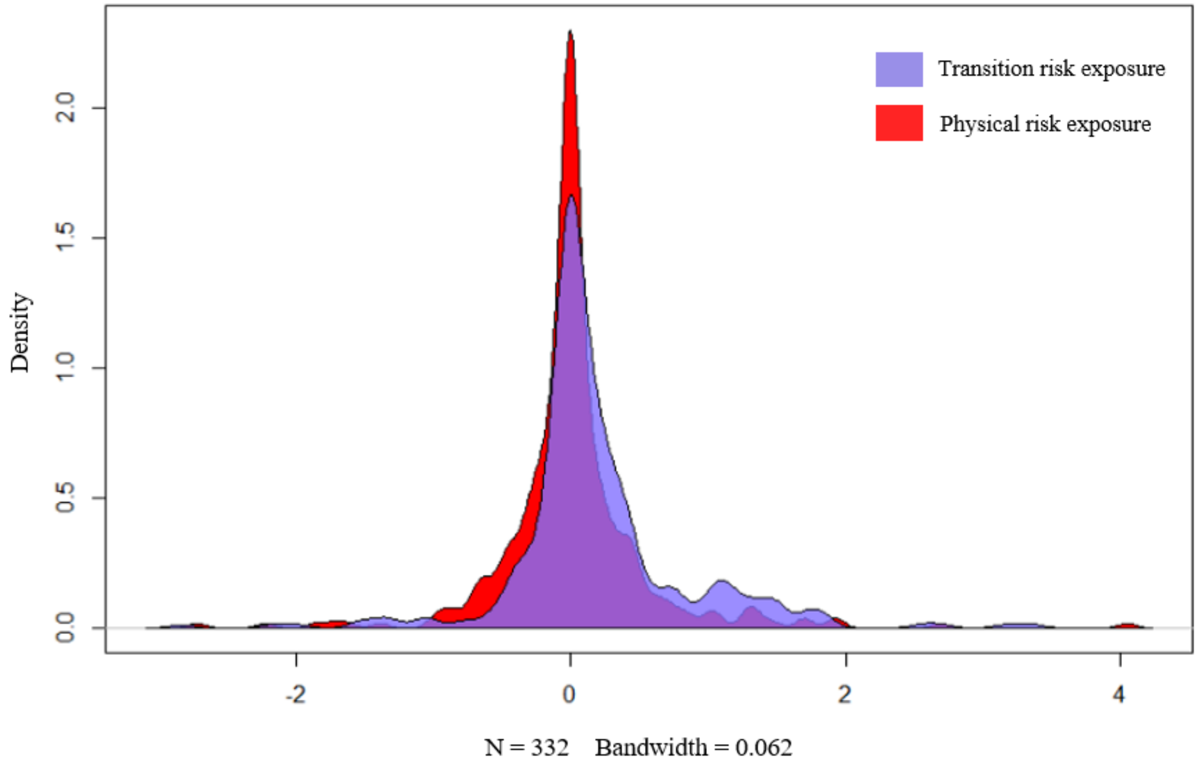

Table 1

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 $\widehat{\Omega}_1$. The acronyms REITs 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	$\hat{X}_1$
Banco Santander	Banks	8,3%	Banco Santander	Banks	7,8%
Bank Polska Kasa Opieki	Banks	8,4%	Barclays	Banks	7,6%
Barclays	Banks	8,3%	BBVA	Banks	7,6%
BBVA	Banks	8,1%	BNP	Banks	7,8%
BNP	Banks	7,9%	Credit Agricole	Banks	8,0%
CRCAM de Normandie	Banks	8,7%	DNB Bank	Banks	7,8%
Credit Agricole	Banks	8,2%	Erste Group Bank	Banks	8,1%
Erste Group Bank	Banks	9,2%	KBC Ancora	Banks	7,7%
Intesa Sanpaolo	Banks	8,3%	KBC Group	Banks	7,5%
Investec	Banks	8,4%	Lloyds Banking Group	Banks	7,5%
Jyske Bank	Banks	7,9%	Nordea Bank	Banks	7,9%
Komercni Banka	Banks	8,0%	OTP Bank	Banks	7,5%
Nordea Bank	Banks	8,8%	Societe Generale	Banks	8,3%
PKO Bank	Banks	8,1%	Unicredit	Banks	7,7%
Societe Generale	Banks	8,8%	Eurazeo	Financial Services	8,2%
Sparebank 1 Helgeland	Banks	8,2%	GBL New	Financial Services	8,1%
Sparebank 1 SMN Ords	Banks	8,7%	Industrivarden A	Financial Services	7,7%
Unicredit	Banks	8,0%	Intermediate Capital Group	Financial Services	7,7%
Vontobel Holding	Banks	8,2%	Peugeot Invest	Financial Services	7,8%
Eurazeo	Financial Services	8,5%	Wendel	Financial Services	8,3%
Intermediate Capital Group	Financial Services	8,2%	Aviva	Life Insurance	7,6%
Peugeot Invest	Financial Services	8,7%	Legal and General	Life Insurance	8,1%
Wendel	Financial Services	8,4%	Prudential	Life Insurance	7,6%
CNP Assurances	Life Insurance	8,7%	Swiss Life Holding	Life Insurance	7,5%
Storebrand	Life Insurance	7,9%	Allianz	Nonlife Insurance	7,8%
Nexity	REIS	7,9%	AXA	Nonlife Insurance	8,0%
Olav Thon Eiendomsselskap	REIS	8,0%	Helvetia Holding N	Nonlife Insurance	7,7%
Hammerson	REITS	8,1%	Mapfre	Nonlife Insurance	7,4%
Land Securities Group	REITS	8,2%	Sampo 'A'	Nonlife Insurance	8,0%
Unibail Rodamco	REITS	7,9%	Vienna Insurance Group A	Nonlife Insurance	7,7%

Table 2

Model selection.

This table performs diagnostic tests for model selection and error distribution assumptions (see Equation 8). 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
GJR-GARCH	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
	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	Skew-normal	6,943	7,023	6,942	6,976
GJR-GARCH		**6,909**	**7,005**	**6,908**	**6,948**
E-GARCH		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

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

Table 3

Correlation matrix for risk factors.

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

	BMG	VMS	MKT	SMB	HML	RMW	CMA	WML	RR	ML	DP	YC	NS
VMS	8%												
MKT	2%	21%											
SMB	7%	6%	12%										
HML	-20%	10%	38%	10%									
RMW	1%	-5%	32%	6%	47%								
CMA	21%	17%	32%	11%	-1%	15%							
WML	23%	15%	27%	12%	21%	23%	16%						
RR	-4%	-13%	3%	2%	14%	11%	-11%	11%					
ML	-5%	-6%	30%	15%	10%	31%	13%	11%	12%				
DP	-1%	12%	41%	4%	5%	16%	30%	1%	-31%	15%			
YC	-2%	10%	1%	0%	2%	1%	0%	0%	-2%	13%	4%		
NS	-4%	16%	16%	-4%	17%	-4%	1%	8%	-6%	3%	-1%	19%	
ES	-6%	24%	48%	19%	63%	11%	12%	19%	-4%	6%	21%	0%	17%

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	0.0%	0.2%		1,626		446,032		22%
Beverages	1	1	0.1%	0.0%	2,471	593	88	70,292	0.02%	15%
Chemicals		27	0.0%	7.8%		7,750		3,932,167		62%
Construction and Mat.	7	15	0.1%	2.2%	491	4,000	4,038	2,556,202	0.34%	144%
Electricity	4	35	0.5%	15.3%	2,817	11,679	1,207	10,411,782	0.12%	141%
Electronic Equipment	7	1	0.2%	0.1%	654	1,935	1,881	485,900	0.39%	41%
Fixed Line Telecom.	7	7	1.7%	0.7%	5,683	2,492	10,713	353,920	0.30%	45%
Food and Drug Retail	7		1.3%	0.0%	4,286		14,334		0.27%	
Food Producers	1	17	0.1%	1.0%	2,615	1,611	1,970	7,547,522	0.28%	680%
Forestry and Paper	1	14	0.0%	1.8%	181	3,460	0	1,237,697	0.00%	59%
Gas, Water	1	12	0.0%	7.8%	740	17,428	1,842	24,236,625	0.51%	118%
General Industrials	2	18	0.3%	2.0%	3,294	2,927	7,725	2,668,725	0.49%	52%
General Retailers	37	2	5.3%	0.0%	3,382	575	10,926	174,412	0.27%	21%
Health Care	13	5	2.0%	0.6%	3,719	3,465	3,517	183,066	0.28%	38%
Household Goods	9	2	0.8%	0.1%	2,034	710	5,293	174,499	0.31%	27%
Industrial Engineering	3	1	0.6%	0.0%	4,957	156	26,792	26,760	0.35%	20%
Metals and Mining		17	0.0%	1.7%		2,711		5,989,661		13872%
Industrial Transport.	7	30	1.5%	4.0%	5,204	3,550	31,017	2,431,281	0.32%	169%
Leisure Goods	4		0.2%	0.0%	1,211		819		0.24%	
Media	32	1	5.3%	1.3%	3,916	35,388	6,940	114,084	0.29%	37%
Mining		36	0.0%	11.2%		8,295		3,162,160		2369%
Oil and Gas Prod.		41	0.0%	26.3%		17,112		7,072,139		121%
Oil Equipment	2	17	0.2%	1.9%	2,639	2,955	290	938,869	0.10%	113%
Personal Goods	13	3	28.0%	0.1%	50,977	554	44,366	963,673	0.29%	29%
Pharmaceuticals	12	9	10.2%	2.0%	20,230	5,827	8,767	100,642	0.22%	62%
Software	108	4	12.7%	0.2%	2,777	1,020	3,091	1,241,990	0.32%	1138%
Support Services	21	6	1.7%	0.4%	1,902	1,793	6,334	574,565	0.23%	53%
Technology Hardware	14	3	2.4%	0.1%	4,061	1,328	11,540	217,997	0.27%	34%
Travel and Leisure	15	31	2.1%	3.6%	3,240	3,111	7,804	2,634,532	0.25%	105%
Unclassified	80	49	22.1%	7.4%	6,550	4,032	6,718	8,025,306	0.27%	209%
Total	414	414	100%	100%	19,115	10,703	17,895	7,136,674	0.28%	618%

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	0,8%	1,9%	2 319	5 305	31	62
Alternative Energy	4	6	0,6%	0,0%	785	138	35	67
Automobiles and Parts	6	1	1,1%	0,0%	995	1	33	73
Beverages	8	4	2,3%	0,1%	1 606	742	33	65
Chemicals	7	10	0,6%	5,1%	458	10 147	33	62
Construction and Materials	19	18	2,2%	1,3%	635	1 460	33	62
Electricity	8	2	0,7%	0,8%	467	7 948	32	62
Electronic and Electrical Equipment	5	3	0,9%	0,0%	1 022	320	31	68
Fixed Line Telecommunications	6	4	2,2%	0,7%	2 004	3 715	27	60
Food and Drug Retailers	4	2	1,6%	0,1%	2 161	552	33	65
Food Producers	20	16	6,3%	0,7%	1 731	880	31	64
Forestry and Paper	5	3	2,2%	0,2%	2 455	1 404	32	61
Gas, Water and Multiutilities		3	0,0%	0,5%		3 544		63
General Industrials	13	11	1,1%	1,2%	473	2 193	32	63
General Retailers	25	8	5,4%	0,1%	1 176	207	33	62
Health Care Equipment and Services	20	11	5,6%	3,1%	1 522	5 527	33	61
Household Goods and Home Construction	16	7	3,3%	0,2%	1 126	504	33	62
Industrial Engineering	14	7	4,0%	0,8%	1 560	2 209	34	63
Industrial Metals and Mining	7	6	0,8%	0,1%	598	490	30	63
Industrial Transportation	18	15	15,6%	4,7%	4 759	6 238	33	64
Leisure Goods	6	4	0,2%	0,3%	202	1 406	32	62
Media	5	25	0,1%	5,0%	110	3 996	30	62
Mining	19	22	0,4%	0,1%	118	104	32	63
Oil and Gas Producers	12	9	2,7%	13,0%	1 232	28 821	32	64
Oil Equipment and Services	7	6	0,4%	0,2%	292	568	30	65
Personal Goods	3	8	0,9%	0,7%	1 691	1 644	35	64
Pharmaceuticals and Biotechnology	42	24	6,8%	14,8%	892	12 245	31	62
Software and Computer Services	39	37	6,0%	9,1%	836	4 888	31	61
Support Services	11	14	1,6%	4,3%	772	6 042	34	61
Technology Hardware and Equipment	25	16	1,9%	4,7%	427	5 875	32	62
Travel and Leisure	15	21	5,6%	2,8%	2 056	2 606	32	61
Unclassified	99	91	16,1%	23,3%	888	5 095	31	62
Total	490	421	100%	100%	1 786	9 293	32	62

Table 5

Descriptive statistics of financial institutions.

This table reports the summary statistics of the financial institutions in our sample. Appendix A presents variable definitions. The sample comprises all European financial institutions from 2005 to 2022, with a market capitalization above €100 million as of June 2022.

	N	Mean	SD	Median	P25	P75
$\hat{\beta}_{VMS}$	5,757	0.017	0.500	-0.004	-0.166	0.142
$\hat{\beta}_{BMG}$	5,757	0.177	0.572	0.051	-0.039	0.341
LogMarketValue	5,757	6.818	1.860	6.705	5.451	8.012
NetIncome	5,757	0.025	0.058	0.010	0.004	0.041
MtoB	5,757	1.291	1.095	1.004	0.668	1.526
Cash	5,757	0.088	0.134	0.035	0.011	0.107
Beta	5,757	0.831	0.558	0.780	0.392	1.180
Scope3 Emissions	1,959	6.907	8.062	3.512	0.853	11.327
Equator Principles Signatory	2,637	0.100	0.301	0.000	0.000	0.000
Board LT incentives	5,624	0.033	0.179	0.000	0.000	0.000
CO2 Disclosure	5,757	0.267	0.442	0.000	0.000	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 REITs and REIS stand for "Real Estate Investment Trusts" and "Real Estate Investment Services", respectively. The Code corresponds to the Datastream symbol.

Financial institutions	Code	Sector	Country	$\hat{\beta}_{BMG}$	
Banca Carige	I:CRG	Banks	Italy	1.80*	(0.92)
Bank of Ireland Group	IE:BIRG	Banks	Ireland	3.36***	(1.15)
Barclays	BARC	Banks	United Kingdom	1.05***	(0.37)
Lloyds Banking Group	LLOY	Banks	United Kingdom	1.49**	(0.68)
Permanent TSB Group Holdings	IE:IL0A	Banks	Ireland	1.81*	(0.97)
Sparebanken Vest	N:SVEG	Banks	Norway	1.10*	(0.64)
Brewin Dolphin	BRW	Financial Services	United Kingdom	1.13*	(0.58)
Hellenic Exchanges Holdings	G:HEL	Financial Services	Greece	1.32*	(0.72)
Intermediate Capital Group	ICP	Financial Services	United Kingdom	1.67***	(0.63)
Lebon	F:LBON	Financial Services	France	1.18**	(0.52)
Saint James's Place	STJ	Financial Services	United Kingdom	1.03**	(0.42)
Aviva	AV.	Life Insurance	United Kingdom	1.15**	(0.52)
Legal and General	LGEN	Life Insurance	United Kingdom	1.50***	(0.53)
Prudential	PRU	Life Insurance	United Kingdom	1.01*	(0.56)
AXA	F:MIDI	Nonlife Insurance	France	1.51**	(0.65)
FBD Holdings	IE:EG7	Nonlife Insurance	Ireland	1.34*	(0.77)
Sampo 'A'	M:SAMA	Nonlife Insurance	Finland	0.92**	(0.39)
Swiss Re	S:SREN	Nonlife Insurance	Switzerland	1.51*	(0.79)
Boot (Henry)	BOOT	REIS	United Kingdom	2.70***	(0.89)
Echo Investment	PO:ECH	REIS	Poland	1.15*	(0.69)
Grainger	GRI	REIS	United Kingdom	1.29**	(0.64)
JM	W:JMBF	REIS	Sweden	1.80**	(0.80)
Nexity	F:NXI	REIS	France	1.38**	(0.65)
Risanamento	I:RN	REIS	Italy	1.73*	(0.93)
British Land	BLND	REITs	United Kingdom	1.01***	(0.38)
Carmila	F:CARM	REITs	France	3.17*	(1.88)
Land Securities Group	LAND	REITs	United Kingdom	0.93**	(0.37)
Unibail Rodamco	H:UBL	REITs	France	1.24***	(0.41)
Unite Group	UTG	REITs	United Kingdom	1.45**	(0.69)

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	$\hat{\beta}_{VMS}$	
Aareal Bank	D:ARL	Banks	Germany	1.01**	(0.44)
Investec	INVP	Banks	United Kingdom	0.66***	(0.13)
Sandnes Sparebank	N:SADG	Banks	Norway	1.32***	(0.49)
Sparebank 1 Helgeland	N:HELG	Banks	Norway	0.19***	(0.06)
Sparebank 1 Nord-Norge	N:NONG	Banks	Norway	0.33**	(0.13)
Sparebank 1 SMN Ords	N:MING	Banks	Norway	0.44***	(0.17)
Sparebanken More	N:MORG	Banks	Norway	0.24*	(0.09)
Sparebanken Vest	N:SVEG	Banks	Norway	1.38**	(0.58)
Swedbank A	W:SWED	Banks	Sweden	0.44***	(0.17)
Vseobec Uver Bank	SK:VUB	Banks	Slovakia	0.47**	(0.23)
Aker	N:AKER	Financial Services	Norway	2.69***	(0.89)
Gimv	B:GIM	Financial Services	Belgium	0.16*	(0.09)
Impax Asset Management Group	IPX	Financial Services	United Kingdom	0.36**	(0.16)
Oresund Investment	W:ORF	Financial Services	Sweden	0.56**	(0.25)
Ratos B	W:RTBF	Financial Services	Sweden	0.18*	(0.09)
Saint James's Place	STJ	Financial Services	United Kingdom	0.64*	(0.33)
Personal Group Holdings	PGH	Nonlife Insurance	United Kingdom	0.27**	(0.13)
Castellum	W:CAST	REIS	Sweden	0.30***	(0.10)
Deutsche Euroshop	D:DEQ	REIS	Germany	1.91***	(0.54)
Fastighets Balder B	W:BALB	REIS	Sweden	0.16**	(0.07)
JM	W:JMBF	REIS	Sweden	1.05***	(0.34)
Nexity	F:NXI	REIS	France	0.58**	(0.28)
Olav Thon Eiendomsselskap	N:OLT	REIS	Norway	0.45***	(0.13)
Risanamento	I:RN	REIS	Italy	1.29**	(0.58)
Retail Estates	B:RET	REITs	Belgium	1.48*	(0.77)
Unibail Rodamco	H:UBL	REITs	France	1.32***	(0.42)
Warehouses de Pauw	B:WDP	REITs	Belgium	0.13*	(0.07)
Wereldhave Belgium	B:WEHB	REITs	Belgium	1.68*	(0.88)

Table 8

Determinants of systemic risk.

This table presents the determinants of systemic risk. Panel A presents the time-series analysis, as described in Equation (4). We use $\widehat{\Omega}_1$, the systemic risk measures derived from the first principal component defined in Equation (2), as the dependent variable. Newey-West standard errors are reported in parentheses. ***, **, and * indicate significance at the 1%, 5% and 10% levels, respectively. In the regressions, a positive coefficient associated with one of the explicative variables indicates that a deterioration in the indicator leads to an increase in systemic risk.

Panel A: Time-series analysis

VARIABLES	(1) $\widehat{\Omega}_1$	(2) $\widehat{\Omega}_1$	(3) $\widehat{\Omega}_1$	(4) $\widehat{\Omega}_1$
BMG	2.333*** (0.692)	1.878*** (0.634)	2.181* (1.173)	1.442*** (0.518)
VMS	1.070 (1.022)	0.831 (0.860)	1.146 (0.779)	0.288 (0.424)
MKT	3.296*** (0.369)	3.213*** (0.440)		2.667*** (0.443)
SMB	5.675*** (1.724)	5.363*** (1.633)		3.091** (1.400)
HML	6.736*** (2.736)	6.810*** (2.275)		2.373* (1.325)
RMW		-1.851 (3.955)		3.644 (2.617)
CMA		0.394 (0.666)		0.288 (0.418)
WML		0.542** (0.249)		0.493*** (0.174)
RR			2.088*** (0.585)	-0.128 (0.416)
ML			32.297 (20.273)	6.035 (5.411)
DP			0.943** (0.477)	-0.827** (0.340)
YC			-0.289 (1.331)	0.541 (0.844)
NS			3.155** (1.503)	0.428 (1.147)
ES			2.229*** (0.206)	1.295*** (0.199)
Constant	-0.060 (0.289)	-0.066 (0.274)	-0.063 (0.316)	-0.055 (0.238)
Observations	207	207	207	207
R-squared	0.805	0.812	0.684	0.893
Adjusted R-squared	0.800	0.804	0.671	0.885

Panel B and C present the cross-sectional analysis, as described in Equation (5). 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 (4) when we replace $\widehat{\Omega}_1$ by the VaR of each financial institution. In Panel B, White heteroskedasticity-robust standard errors are reported in parentheses. In Panel C, we include industry and country fixed effects and report clustered standard errors.

Panel B: Cross-sectional analysis

VARIABLES	(1) $\hat{X}_1$	(2) $\hat{X}_1$	(3) $\hat{X}_1$	(4) $\hat{X}_1$
$\hat{\beta}_{BMG}$	0.007**	0.005**	0.005**	0.005**
	(0.003)	(0.003)	(0.002)	(0.003)
$\hat{\beta}_{VMS}$	-0.001	0.003	0.001	-0.004
	(0.003)	(0.003)	(0.003)	(0.003)
$\hat{\beta}_{MKT}$	0.029***	0.024***		0.032***
	(0.004)	(0.005)		(0.004)
$\hat{\beta}_{SMB}$	0.003**	0.002*		-0.001
	(0.001)	(0.001)		(0.001)
$\hat{\beta}_{HML}$	0.009***	0.012***		0.007***
	(0.002)	(0.002)		(0.003)
$\hat{\beta}_{RMW}$		0.001		0.001
		(0.001)		(0.001)
$\hat{\beta}_{CMA}$		0.001		0.009***
		(0.003)		(0.002)
$\hat{\beta}_{WML}$		0.027***		0.003
		(0.007)		(0.006)
$\hat{\beta}_{RR}$			-0.002	-0.008***
			(0.002)	(0.003)
$\hat{\beta}_{ML}$			0.0005***	0.0004**
			(0.0002)	(0.0002)
$\hat{\beta}_{DP}$			0.005*	-0.014***
			(0.003)	(0.003)
$\hat{\beta}_{YC}$			0.002	-0.002
			(0.002)	(0.002)
$\hat{\beta}_{NS}$			0.001	-0.004***
			(0.001)	(0.001)
$\hat{\beta}_{ES}$			0.078***	0.042***
			(0.009)	(0.009)
Constant	0.019***	0.018***	0.021***	0.012***
	(0.003)	(0.003)	(0.003)	(0.003)
Observations	332	332	332	332
R-squared	0.262	0.285	0.254	0.389
Adjusted R-squared	0.250	0.268	0.236	0.362

Panel C: Cross-sectional analysis with fixed effects and clustered standard errors

VARIABLES	(1) $\hat{X}_1$	(2) $\hat{X}_1$	(3) $\hat{X}_1$
$\hat{\beta}_{BMG}$	0.006* (0.003)	0.005* (0.003)	0.006** (0.002)
$\hat{\beta}_{VMS}$	-0.002 (0.002)	-0.002 (0.004)	-0.001 (0.003)
$\hat{\beta}_{MKT}$	0.029*** (0.001)	0.030*** (0.005)	0.026*** (0.002)
$\hat{\beta}_{SMB}$	0.0002 (0.001)	-0.001 (0.001)	0.0003 (0.002)
$\hat{\beta}_{HML}$	0.006 (0.003)	0.006** (0.003)	0.006 (0.003)
$\hat{\beta}_{RMW}$	0.001 (0.001)	0.001 (0.001)	0.001 (0.002)
$\hat{\beta}_{CMA}$	0.009*** (0.002)	0.008*** (0.002)	0.008*** (0.002)
$\hat{\beta}_{WML}$	0.003 (0.005)	0.003 (0.008)	0.004 (0.009)
$\hat{\beta}_{RR}$	-0.008** (0.002)	-0.009** (0.004)	-0.010*** (0.002)
$\hat{\beta}_{ML}$	0.0004 (0.0002)	0.0003 (0.0002)	0.0003 (0.0003)
$\hat{\beta}_{DP}$	-0.012** (0.003)	-0.012** (0.004)	-0.011** (0.003)
$\hat{\beta}_{YC}$	-0.001 (0.002)	-0.002 (0.002)	-0.0005 (0.002)
$\hat{\beta}_{NS}$	-0.004*** (0.001)	-0.004*** (0.001)	-0.004*** (0.001)
$\hat{\beta}_{ES}$	0.045*** (0.011)	0.044*** (0.012)	0.046*** (0.011)
Observations	332	332	332
R-squared	0.424	0.432	0.470
Adjusted R-squared	0.389	0.356	0.389
FE : Country	No	Yes	Yes
FE : Industry	Yes	No	Yes

Table 9

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 (4) by replacing $\widehat{\Omega}_1$ with the VaR of each financial institution. Appendix A presents variable definitions. Heteroskedasticity-robust standard errors are reported in parentheses. ***, **, and * indicate significance at the 1%, 5% and 10% levels, respectively.

VARIABLES	(1) $\hat{\beta}_{BMG}$	(2) $\hat{\beta}_{BMG}$	(3) $\hat{\beta}_{BMG}$	(4) $\hat{\beta}_{BMG}$
Log MarketValue	0.0207*** (0.00495)	0.0324*** (0.0115)	0.0430*** (0.00998)	0.0218*** (0.00510)
NetIncome	-0.268 (0.174)	-0.276 (0.502)	0.0953 (0.230)	-0.250 (0.177)
MtoB	0.00527 (0.00795)	-0.0210 (0.0162)	0.0255** (0.0121)	0.00668 (0.00803)
Cash	-0.127* (0.0658)	-0.492** (0.197)	0.233* (0.120)	-0.119* (0.0674)
Beta	0.0702*** (0.0180)	0.0870*** (0.0285)	0.0786*** (0.0268)	0.0801*** (0.0184)
Scope3 Emissions		0.00514** (0.00203)		
Equator Principles Signatory			-0.0828** (0.0326)	
Board LT incentives				-0.122*** (0.0396)
Constant	-0.207*** (0.0774)	-0.494*** (0.0991)	-0.775*** (0.115)	-0.239*** (0.0792)
Observations	5,757	1,959	2,637	5,624
R-squared	0.172	0.301	0.275	0.175
Adjusted R-squared	0.167	0.292	0.266	0.170
FE : Country	Yes	Yes	Yes	Yes
FE : Industry	Yes	Yes	Yes	Yes

Table 10

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 (4) by replacing $\widehat{\Omega}_1$ with the VaR of each financial institution. Appendix A presents variable definitions. Heteroskedasticity-robust standard errors are reported in parentheses. ***, **, and * indicate significance at the 1%, 5% and 10% levels, respectively.

VARIABLES	(1) $\hat{\beta}_{VMS}$	(2) $\hat{\beta}_{VMS}$	(3) $\hat{\beta}_{VMS}$
Log MarketValue	-0.0111*** (0.00430)	-0.0372*** (0.00776)	-0.0103** (0.00451)
NetIncome	-0.0440 (0.130)	0.191 (0.199)	-0.0626 (0.133)
MtoB	-0.00181 (0.00662)	0.0180* (0.00991)	0.000390 (0.00668)
Cash	0.255*** (0.0620)	-0.00129 (0.0718)	0.235*** (0.0623)
Beta	-0.0747*** (0.0160)	-0.0984*** (0.0213)	-0.0692*** (0.0161)
Equator Principles Signatory		-0.112*** (0.0338)	
Board LT incentives			-0.129*** (0.0389)
Constant	0.299*** (0.0504)	0.689*** (0.0749)	0.289*** (0.0519)
Observations	5,757	2,637	5,624
R-squared	0.171	0.247	0.173
Adjusted R-squared	0.166	0.238	0.168
FE : Country	Yes	Yes	Yes
FE : Industry	Yes	Yes	Yes

Table 11

Tail climate risk and carbon disclosure.

This table presents estimates of the effect of tail climate transition risk on carbon disclosure. In columns (1) to (3), $\hat{\beta}_{BMG}$ is a static institution-level measure of tail transition risk. In columns (4) to (6), $\hat{\beta}_{BMG}$ is an institution-level measure of tail transition risk defined on three-year windows. Regressions (1) to (4) use a linear probability model. Regressions (5) and (6) use 2SLS regressions, where the average value of $\hat{\beta}_{BMG}$ at the sector-year level is used as an instrument for $\hat{\beta}_{BMG}$ in the first stage. Appendix A presents variable definitions. Standard errors are clustered at the financial institution level and reported in parentheses. ***, **, and * indicate significance at the 1%, 5% and 10% levels, respectively.

VARIABLES	(1) CO2 Disclosure (t)	(2) CO2 Disclosure (t)	(3) CO2 Disclosure (t)	(4) CO2 Disclosure (t)	(5) CO2 Disclosure (t)	(6) CO2 Disclosure (t)
	Linear Probability Model				*2SLS*	
$\hat{\beta}_{BMG}$	0.0553**	0.0485***	0.0453**	0.00838*	0.113**	0.112**
	(0.0227)	(0.0187)	(0.0188)	(0.00429)	(0.0446)	(0.0444)
LogMarketValue (t-1)	0.120***	0.121***	0.117***	0.0286**	0.0379***	0.0251*
	(0.00563)	(0.00552)	(0.00571)	(0.0117)	(0.0132)	(0.0149)
NetIncome (t-1)	-0.00697	-0.120	-0.0394	0.0746	-0.0556	-0.0328
	(0.131)	(0.117)	(0.113)	(0.0975)	(0.147)	(0.147)
MtoB (t-1)	-0.00175	-0.0195**	-0.0163*	-0.0185*	-0.0350***	-0.0304**
	(0.0121)	(0.00971)	(0.00875)	(0.0102)	(0.0132)	(0.0140)
Cash (t-1)	0.0177	-0.0274	0.141*	0.0230	0.0285	0.0222
	(0.0811)	(0.0722)	(0.0722)	(0.0679)	(0.0682)	(0.0682)
Beta (t-1)	0.114***	0.0958***	0.108***	0.0271	0.0244	0.0171
	(0.0212)	(0.0199)	(0.0196)	(0.0200)	(0.0233)	(0.0236)
Constant	-0.710***	-0.810***	-0.778***	0.0505	-0.0875	0.0992
	(0.0455)	(0.0508)	(0.0634)	(0.0830)	(0.123)	(0.105)
Observations	5,454	5,454	5,454	5,454	5,454	5,454
R-squared	0.417	0.481	0.496	0.653		
FE : Country	No	Yes	Yes	No	Yes	No
FE : Financial Institution	No	No	No	Yes	No	Yes
FE : Industry	No	No	Yes	No	Yes	No
FE : Year	Yes	Yes	Yes	Yes	Yes	Yes

Appendix A. Variable definitions

Variable	Description
Beta	Equity beta (897E in Datastream).
BMG	Transition risk factor, 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).
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).
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).
Equator Principles	Dummy variable equal to one if the financial institution has signed (from ENPIDP036 in Refinitiv ESG).
ES	Economic Sentiment indicator (Eurostat).
HML	Difference between the returns on portfolios of high and low book-to-market stocks (High-Minus-Low factor) from Kenneth French website library.
LogMarketValue	Natural logarithm of market capitalization (item MV in Datastream, expressed in million euros).
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.
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).
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 10-year rates (European Central Bank).
RMW	Difference between the returns of robust and weak stocks (Robust-Minus-Weak factor) from Kenneth French website library.
RR	Risk Reversal on the USD/EUR options from Bloomberg.
Scope3 Emissions	Ratio of Scope3 emissions in tons (from Carbone 4) to sales (WC01001 in Worldscope Datastream, expressed in thousand euros).
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 alive stocks reported in Refinitiv Eikon and listed on European equity markets (excluding financial sector companies). We use the firm-level composite physical risk score from Trucost, which aggregates the scores of seven hazards (coldwave, flood, heatwave, hurricane, sea-level rise, water stress, wildfire) using a 2050-horizon moderate-intensity climate change scenario.
WML	Difference between the returns on portfolios of 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 (European Central Bank).