Systemic Climate Risk

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Abstract

This paper introduces a novel market-based framework to study the effects of tail climate risks in the financial sector. Beyond identifying financial institutions most vulnerable to physical and transition climate risks, our framework explores the potential for these risks to induce contagion effects within the financial sector. Based on the securities of large European financial institutions spanning 2005 to 2022, we show that, unlike physical risks, transition risks significantly and increasingly influence systemic risk in the financial sector. We find that financial institutions with cleaner investment and lending portfolios and with a long-term orientation exhibit lower exposure to transition risks, providing valuable guidance to financial institutions and regulators in addressing climate-related financial risks.

JEL Classification: G10, G20, G32, Q54

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

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Abstract

This paper introduces a novel market-based framework to study the effects of tail climate risks in the financial sector. Beyond identifying financial institutions most vulnerable to physical and transition climate risks, our framework explores the potential for these risks to induce contagion effects within the financial sector. Based on the securities of large European financial institutions spanning 2005 to 2022, we show that, unlike physical risks, transition risks significantly and increasingly influence systemic risk in the financial sector. We find that financial institutions with cleaner investment and lending portfolios and with a long-term orientation exhibit lower exposure to transition risks, providing valuable guidance to financial institutions and regulators in addressing climate-related financial risks.

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1. Introduction

In 2015, the Governor of the Bank of England, Mark Carney, warned that climate change had the potential to profoundly affect asset prices and financial stability (Carney, 2015). 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 typically categorized into two main types: physical risks and transition risks.[1] These risks can have a negative and differentiated impact on financial institutions, leading to losses in the value of financial portfolios, heightened claims paid by insurers, or diminished creditworthiness of borrowers. These direct impacts of climate risks on financial institutions are referred to as "first-round" effects. Furthermore, climate shocks can pose a threat to financial stability if they occur simultaneously, affecting a large number of financial institutions, or if an extreme shock is transmitted to other institutions through the network of financial interconnections. This underscores the potential for climate-related shocks to jeopardize financial stability by affecting interconnected institutions, giving rise to contagion effects, also referred to as "second-round" effects. We term the combined first- and second-round threats posed to the financial system by climate hazards as "systemic climate risks."

In this article, we introduce an innovative market-based framework to assess the influence of climate risks on systemic risk within the financial sector. The rationale for adopting a market-based approach lies in the belief that climate risks should prompt a repricing of securities held by financial institutions. Our framework can serve as a valuable tool for pinpointing *which* financial institutions are the most vulnerable to climate risks and exploring strategies for both

[1] Physical risks stem from the effects of climate change and climate-related hazards (e.g., heat waves, extreme precipitation, wildfires, etc.). Transition risks arise 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).

institutions and policymakers to mitigate systemic climate risks. Contemporaneous studies focus on the first-round effects of climate risks on financial institutions (e.g., Alessi et al., 2021; Jung et al., 2021; Ojea-Ferreiro et al., 2022). These approaches assume independence among financial institutions and overlook the potential contagion effects of climate shocks within the financial sector. To our knowledge, our market-based framework represents the first attempt to propose a test procedure for detecting and quantifying the second-round effects of climate risks on financial institutions, which is a key element in assessing the level of systemic risk in the financial sector (e.g., Billio et al., 2012; Duarte and Eisenbach, 2021)[2]. Indeed, common holdings of different market participants, direct interdependencies among financial institutions, and potential fire-sale dynamics may amplify the impact of climate risks on financial stability. Based on our framework, we estimate the effects of both transition and physical risks on various types of financial institutions—banks, insurers, financial services companies, and real estate investment firms—as well as on various countries, capturing both cross-border and cross-sectoral transmission and amplification channels. Therefore, in contrast to existing literature, we aim to provide a comprehensive evaluation of systemic climate risks in the financial sector.

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). The specificity of our approach lies in its ability to discern between two fundamental elements of systemic risk: individual tail risks and tail dependencies. This distinction proves crucial for studying and differentiating the first- and second-round effects of climate risks on the financial sector. Moreover, our approach enables the estimation of covariations in tail risks among a vast array of financial institutions, thereby reflecting both cross-sectoral and cross-border shocks. Using market data, we derive time-varying measures of

[2] See also here.

individual tail risks for each financial institution, coupled with a dynamic indicator of systemic risk that captures common shifts in financial institution tails. Our methodology thus offers a comprehensive view of both individual and interconnected risk dynamics.

Second, we construct tail transition and physical risk factors that aim to capture changes in the expected impact of extreme climate shocks on the value of nonfinancial firms to which financial institutions are exposed through loans, portfolio holdings, or insurance contracts. Using a large sample of dead and active stocks issued by nonfinancial companies, we sort companies according to specific climate characteristics and build long-short factor mimicking portfolios. Tail risk factors are then derived from the returns of the long-short portfolios, employing a GARCH model. We use these tail risk factors in a regression scheme to analyze the sensitivity of financial institutions to extreme climate shocks through their exposures to nonfinancial firms. This sensitivity 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.

Third, we introduce a two-pass test procedure to assess whether climate risks exacerbate tail risk dependence among financial institutions. Our procedure builds upon the literature exploring the use of principal components in asset pricing (e.g. Giglio and Xu, 2021; Kozak et al., 2018; Pukthuangthong et al., 2019) to assess whether risk factors are linked to stock return comovements. Our procedure is tailored to the examination of the determinants of tail risk dependencies. In the first phase of our test procedure, based on a time series regression, we 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

[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.

cross-sectional information on individual climate risk exposures and on individual contributions to systemic risk. The objective of this complementary test is to examine whether the institutions most exposed to climate risks contribute more to global downside risk.

Fourth, we investigate the characteristics of 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, and environmental and governance features. We notably include indirect greenhouse gas (GHG) emissions originating from the holding of securities and loans by financial institutions in our list of regressors. We also assess the extent to which our institution-level climate risk indicator correlates with country-level climate characteristics, as well as the effect of various regulatory shocks (nonfinancial disclosure mandates and net-zero transition plans) on our measure. Subsequently, we explore the interaction between various initiatives, particularly the disclosure of environmental information, and our market-based measure of climate risks. In essence, this fourth step seeks to determine whether the pricing of climate risks incorporates extra-financial information and examines how financial institutions react to their climate risk exposure. Understanding the factors affecting individual climate risk exposure is essential for regulators and for financial practitioners, guiding them in taking actions to mitigate systemic climate risks.

Overall, our market-based framework provides a flexible tool for evaluating the emergence of systemic 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. Beyond this, our approach provides valuable insights for financial institutions and supervisors seeking levers to mitigate systemic climate risks. Alternative approaches examine the holdings of brown securities and loans by financial institutions (e.g., Alessi and Battiston, 2022; ECB-ESRB, 2021) or assess firm-level climate risk attention based on discussions in earnings calls (Li et al., 2020; Sautner et al., 2023). Our framework is inherently more closely related to financial outcomes, investigating whether systemic climate risks are reflected in asset prices and whether climate shocks are already propagating to and between financial institutions. Importantly, our climate risk estimates can also reflect the fact that investors are likely to respond more acutely to climate shocks in times of crisis, when financial institutions are most vulnerable. Given the forward-looking nature of market prices, our framework can detect warning signals of future financial disruptions due to climate risks. Therefore, our approach should 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), these projections facing inherent uncertainty (Barnett et al., 2020).

We apply our framework to a sample of 371 large European financial stocks, spanning from 2005 to 2022 at a monthly frequency, sourced from Refinitiv Datastream. We focus on Europe rather than the United States for several reasons. First, European investors may have stronger environmental concerns than their American counterparts (see Amel-Zadeh and Serafeim, 2018).[4] Second, an escalation in systemic risk could potentially yield more severe economic consequences in Europe, as the failure of European institutions typically is of large magnitude when compared to the domestic GDP (Engle et al., 2015). Third, it allows us to leverage our access to confidential regulatory data from the Eurosystem on institutional holdings.

[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 that in the US over the period 2014-2020.

Our results indicate that transition risks significantly affect the tail risk of European financial institutions, particularly in the case of life insurance companies and real estate investment trusts. Importantly, we show that transition risks can exacerbate extreme risk dependence within the European financial sector, even if the magnitude of these second-round effects appears moderate. This finding constitutes, to our knowledge, the first empirical evidence of potential contagion effects within the financial sector arising from climate shocks, whether from common risk exposures, spillovers, or pure contagion (Masson, 1998). Using dynamic estimates, we also show that the incorporation of transition risks 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. In 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 perceive the materialization of regulatory risks as more immediate than that of physical risks. This disparity may also be attributed to the limited synchronicity of natural disasters on a European scale. Conversely, transition shocks are more likely to affect many companies simultaneously (Bolton and Kacperczyk, 2021). Moreover, the divergence in physical risk scores among different data providers may lead to 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 Environmental, Social, and Governance scores; see Section 2.2).

Looking at the characteristics of institutions that correlate with climate risks, we find that climate risk exposure is lower for financial institutions that engage in environmentally responsible initiatives. Using Scope 3 GHG data emissions, we also show that institutions with cleaner investment and lending portfolios tend to be less exposed to transition risks. This result not only supports the notion that our individual climate risk estimates effectively capture financial institutions' exposure to transition risks via the investment channel but also suggests that our risk measures may serve to address the scarcity of Scope 3 carbon GHG emission data. In addition, we gauge the long-term orientation of financial institutions through proxies such as institutional ownership and the long-term incentives granted to board members. Our analysis reveals a negative relationship between long-term orientation and transition risk exposure. Our indicators also correlate with country-level climate risk variables and country-year level ESG regulatory shocks. Finally, our results indicate that financial institutions with higher exposure to transition risks tend to disclose more extrafinancial information through flexible channels. Additionally, we observe that financial institutions react to physical risks by undertaking proactive risk management initiatives.

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 articles indicate that climate risks remain underestimated by market participants, leading to market inefficiencies (e.g., Alok et al., 2020; Hong et al., 2019; Kruttli et al., 2021). Our contribution to this literature lies in proposing a flexible framework to assess whether extreme climate risks are reflected in the tail risk of equity markets. While this study is centered on the European financial sector, we believe that the proposed framework can be adapted to other countries, industries, and asset types.

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 outperformed during the global financial crisis, while Ilhan et al. (2021) identify brown stocks as more exposed to tail downside risks based on options market prices. Several articles delve into how certain ESG characteristics may help reduce the extreme risk of banks (Aevoae et al., 2022; Anginer et al., 2018; Kleymenova and Tuna, 2021; Scholtens and van't Klooster, 2019) or equity mutual funds (Cerqueti et al., 2021). In a contemporary study, Jung et al. (2021) develop an individual climate risk measure (CRISK) derived from the SRISK indicator (Brownlees and Engle, 2017), which focuses on the first-round effect of fossil fuel shocks on banks. Related methodologies to assess direct 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 encompasses all types of financial institutions, addressing both transition and physical risks. Second, we introduce a novel individual climate risk measure for financial institutions, the climate exposure CoVaR, derived from Adrian and Brunnermeier's (2016) work. Third and most notably, our paper pioneers the design of a test procedure to analyze whether climate risks affect the overall level of systemic risk in the financial sector, capturing second-round effects. This unique aspect of our framework addresses potential contagion effects across financial institutions, a key element of systemic risk often neglected by the related literature on climate finance.[5]

Finally, our study makes a valuable contribution 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). In addition, by using earnings call transcripts, Li et al. (2020) and Sautner et al. (2023) build firm-level measures of climate risks and investigate which characteristics correlate with these measures as well as how firms

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

respond to such risks. Our research takes a different approach, analyzing the determinants of investors' pricing of corporate climate risks. We find a limited correlation between our measure and that of Sautner et al. (2023) within our sample of financial institutions. This suggests that greater exposure to tail climate risks does not consistently translate into more in-depth discussions of these risks during earnings calls. Furthermore, to the best of our knowledge, our study is the first to explore a broad spectrum of potential characteristics associated with a climate risk measure derived from market data. These include environmental and governance features, Scope 3 greenhouse gas (GHG) emissions, and information on institutional ownership. Finally, we extend the literature on the determinants of voluntary nonfinancial disclosure (e.g., Dhaliwal et al., 2011, Ilhan et al., 2023, Reid and Toffel, 2009) by testing whether financial institutions with high exposure to climate risks are inclined to disclose more information about these risks.

The rest of the paper is organized 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 tail risk of financial institutions. Our baseline measure of tail risk is a time-varying 1-month 95%-value-at-risk (VaR) that we estimate from the stock returns of financial institutions based on a GJR-GARCH model (see Appendix C). A 1-month 95%-VaR represents the negative return that is not exceeded within this month with a 95% probability. Alternative tail risk measures, such as the expected shortfall (ES), can also be used.[6] Equity returns are meant to be informative about the risks of financial institutions and to reflect information more quickly than accounting variables. Furthermore, the use of tail risk measures meets our objective of analyzing whether climate risks threaten financial stability.

Our systemic risk measure shares similarities with that in previous studies, namely, Adams et al. (2014), Adrian et al. (2016), and Kelly and Jiang (2014). Nevertheless, the proposed indicator presents certain discrepancies with existing measures, both in terms of target and methodology, making it more suitable for the needs of our study. First, in contrast with the rest of the literature, our systemic risk measure distinguishes between two important elements of systemic risk: individual tail risks and extreme dependence. We argue that this distinction is essential to study both the first- and second-round effects of climate risks on the financial sector. Second, while the CoVaR indicator of Adrian et al. (2016) examines the contribution of each institution 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 C) of each financial institution and then investigate their comovements. The main originality of our approach 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.[7] This allows us to

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

examine both cross-sectoral and cross-border shock transmission and amplification channels. Finally, our method is linked to that of Kelly and Jiang (2014), who directly estimate common dynamics in the tail risk of firms by using the cross-section of returns. An attractive feature of our measure compared to that of Kelly and Jiang (2014) 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:

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

with $\sum$ being the covariance matrix between the time variations in the VaR of financial institutions. In our framework, we take the VaR in first difference (ΔVaR) which reflects the change in tail risk and ensures 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 demeaned ΔVaR. We perform the principal component analysis on the correlation matrix rather than the covariance matrix because using the covariance may 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 $\xi: [\xi_1, \ldots, \xi_j]$ 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 first principal component provides a dynamic

VaR is that the estimation of tail dependence can be performed on the entire sample instead of a small number of extreme observations.

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 financial institution to $\widehat{\Omega}_1$ are given by $\hat{X}_1$, an $N \times 1$ vector extracted from the $\hat{X}$ matrix. These loadings represent the contribution of each financial institution to downside risk in the financial sector.

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 in the database, compared to 6.5% for the second, which is satisfactory considering the dimensionality of the database. The main results in the rest of the paper are robust to the use of sparse PCA, which helps to manage the high cross-sectional dimensionality of the data by introducing sparsity structures to the input variables. Similarly, the main conclusions remain unchanged when we extract comovements by using dynamic PCA, which has been suggested as a remedy for high-dimensional and time-dependent data.[8] 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 A.1 represents the time-varying systemic risk indicator ($\widehat{\Omega}_1$) for all institutions from February 2005 to April 2022, estimated from the PCA. $\widehat{\Omega}_1$ 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 during 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.

[8] The average correlation between systemic risk indicators obtained from standard PCA, sparse PCA, and dynamic PCA is over 98%.

In addition, Table OA.1 shows the largest contributors to systemic risk. Among the top 30 contributors, banks are the most represented institutions (19 out of 30). Interestingly, the ranking of the most interconnected institutions shows notable differences when we estimate the dependence between returns or tail risk measures. 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 by using investor flows toward sustainable exchange-traded funds. Finally, in some articles, investors' attention to climate risks is explored by building long-short portfolios based on market and environmental variables (e.g., Görgen et al., 2020; Hsu, et al., 2022). We follow the latter approach, as it directly captures the effect of climate characteristics on non-financial equity returns. We then derive tail climate risk factors from long-short portfolio returns.

2.2.1. Factor construction

We construct two climate risk factors by using a large sample of dead and active European stocks (excluding financial sector companies). The factors are based on the monthly returns[9] of long-short portfolios following the standard approach in the asset pricing literature (e.g., Fama and French, 1993, 2015). Each month, we sort nonfinancial stocks into 5 quintile portfolios based on climate characteristics, and then, we 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). To ensure proper portfolio diversification, we construct climate risk factors only at the European level. We recognize that these regional factors may not be able to fully reflect local climate shocks in smaller European countries. On the other hand, such shocks are unlikely to affect the stability of the European financial system. Finally, since we are interested in extreme climate risks and to ensure consistency with the first step (see Section 2.1), we estimate the VaR of each climate risk factor based on a GJR-GARCH model, as described in Appendix C.

In the case of transition risks, the long and short positions are determined by their GHG emission intensity.[10] We use both reported and estimated emissions, Scopes 1 & 2, divided by

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

[10] As pointed out by Giglio et al. (2021), measuring transition risk by using GHG emissions is the most common approach, even if other possibilities exist. We choose to use GHG 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 GHG 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.

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 A.1), the transition risk factor is constructed by using six value-weighted portfolios formed on market capitalization (B for "Big", S for "Small", see Equation 4), book-to-market (H for "High", L for "Low"), and the two lowest and highest deciles of GHG 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 GHG 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 nonfinancial stocks for which data for all characteristics are available. In 2005, data were available for approximately 400 European nonfinancial stocks, compared to 2,070 in 2022. Our study starts in 2005 because there are not enough data available on GHG 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).[11] In contrast with BMG, the correlation between the physical climate risk factor and the "value" factor (HML) is naturally low (see Table A.1), so we filter portfolios based on market capitalization only. Therefore, the physical climate factor is built by 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 with BMG, the allocation of VMS is rebalanced on a monthly basis, but the physical scores are fixed over time.

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

2.2.2. *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 Appendix C. 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, is not exceeded with a given

[11] Using different scenarios, such as the Composite High 2050 score, does not change our results. For a comparison of Trucost scores with scores from other data providers, see Hain, Kölbel, and Leippold (2022).

probability. An increase in tail climate risks may result from a higher risk of correction in GHG-intensive stocks or an increase in the probability of outperformance in low emitters, which is likely to occur in the event of 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 $\Delta\widehat{VaR}_i$ satisfies the following linear factor model:

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

where $\Delta\widehat{VaR}_{i,t}$ represents the estimated variations in extreme risk for each financial institution *i* in period *t* (see Appendix C), 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 may drive the variations in 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 sets of bad times (Ang, 2014; Chinco et al., 2022). For consistency with the dependent variable, we estimate the VaR of these systematic risk factors, which seems well suited to capture the bad states of the world associated with specific risk factors. 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, 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 the contribution of the tail climate risks to each financial institution's stress. We estimate Equation (6) by 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:

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

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

where $\hat{\beta}_{i,t}$ is 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 by 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 type and to compute the respective confidence intervals.

2.4. Two-pass test procedure

In this section, we propose a two-pass regression procedure to evaluate 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 we propose a complementary test that exploits the cross-sectional dimension. From Equation (9), the covariance across $\Delta\widehat{VaR}_i$, denoted $\sum$, is determined by the following relation (after suppressing time subscripts):

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

where β_f and β_g are matrices containing the individual coefficients estimated in Equation (6). Empirically, we find that our model captures 80% of the correlation between changes in the tail risk of financial institutions. To statistically evaluate 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, in which we exploit macro panel data to propose a dynamic estimation of the climate exposure CoVaR, we 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 $\hat{X}_1$, the loadings of each financial institution *i* to $\widehat{\Omega}_1$ (see Equation 3), onto $\hat{\beta}$ estimated in Equation (6):

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

This second regression tests whether the financial institutions most exposed to climate risks have stronger tail dependence on 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 use two standard error estimation methods for time series regressions (Equation 10). Since diagnostic tests indicate the presence of autocorrelation and heteroscedasticity in the residuals, we report robust standard errors based on Newey and West (1987). Moreover, to address the issue of non-normally distributed errors and the moderate sample size, we also estimate the model non-parametrically based on a bootstrapping approach. Because it requires no distribution assumptions, bootstrapping can produce more accurate inferences when data are not behaving well, or when the sample size is small. More specifically, we resample the data with replacement, then generate 10,000 bootstrap replicates of the regression coefficients, and calculate the bias-corrected and accelerated 90% confidence intervals. We report the results of the bootstrapping approach in Table OA.4 (Online Appendix). Regarding the cross-sectional regressions (Equation 11), we report robust standard errors based on White (1980). Then, we estimate Equation (11) with fixed effects for industries and countries and clustered standard errors. Finally, we compute standard errors based on the bootstrapping approach described above (see Table OA.5, Online Appendix).

This second-stage regression uses the loadings from Equation (6), which may contain estimation errors, as regressors. To attenuate the inherent Errors-in-Variables (EIV) bias, we employ the following two approaches. First, we use the Bayesian shrinkage factor of Vasicek (1973) who suggests shrinking each individual estimate toward a prior, depending on the relative precision of the individual coefficient ($\hat{\beta}_i$) and prior ($\hat{\beta}_{sect}$). We obtain a posterior belief of the estimator ($\hat{\beta}_i^{Shr}$) following Equation (12):

$$\hat{\beta}_i^{Shr} = \frac{\sigma_{\beta_{sect}}^2}{\sigma_{\beta_i}^2 + \sigma_{\beta_{sect}}^2}\hat{\beta}_i + \frac{\sigma_{\beta_i}^2}{\sigma_{\beta_i}^2 + \sigma_{\beta_{sect}}^2}\hat{\beta}_{sect} \qquad (12)$$

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

Second, we use the instrumental variables (IV) approach proposed by Jegadeesh et al. (2023). Based on their method, we first estimate individual coefficients from Equation (6) from a random subset representing half of the observations in the data sample. These betas are considered as the "explanatory" variables for the second stage regressions (Equation 11). Then, we estimate individual coefficients (Equation 6) again using the other half of the data sample, and these betas are the "instrumental" variables. Since we estimate the independent and instrumental variables from disjoint data samples, their measurement errors are not cross-correlated. Overall, this IV approach shrinks the individual coefficients used as explanatory variables towards the cross-sectional means of their instruments. We present the results of these two approaches to mitigating EIV bias in Tables OA.6 and OA.7 (Online Appendix).

2.5. Data

2.5.1. Stock market data

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

Based on the remaining list, we download the prices (including dividends) and compute the log returns from the available price series (15,786).[12] We apply several filters recommended by Landis and Skouras (2021) to address implausible returns, illiquidity, and unusually high or low volatility. Specifically, we eliminate from our sample the series for which more than 95% of the returns have the same sign (positive or negative). 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

[12] 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.

eliminate stocks for which the monthly standard deviation of returns is greater than 40% or less than 0.01%. The remaining database contains 12,283 shares, including 9,958 nonfinancial assets. We use nonfinancial assets to construct the climate risk factors, while 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 research (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 nonlife 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 A.2 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 Tables B.1 and B.2).

We retrieve financial characteristics, including market capitalizations, book values of equity, cash holdings, total assets, incomes, net sales, and fixed assets in euros, from Refinitiv Datastream. 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, and the conservative-minus-aggressive factor (CMA) based on investment. Carhart (1997) also proposes the winner-minus-loser factor (WML), which captures a momentum effect. Alternatively, we also use the *q5* factors of Hou et al. (2015, 2021), the nontraded version of the liquidity factor (*LIQ*) of Pástor and Stambaugh (2003), and the quality-minus-junk (*QMJ*) factor of Asness et al. (2019).[13] The q5 factors include 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)[14], Ang (2014) points out that "each factor defines a different set of bad times". For example, Smith

[13] We download Fama and French factors from Kenneth French's website, the q5 factors from the data library at global-q.org, the liquidity factor from Robert Stambaugh's website, and the QMJ factor from AQR Capital's website.
[14] 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.

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 A.1 reports limited correlation across the estimated $\Delta\widehat{VaR}$ of all factors, indicating that they reflect nonoverlapping 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

In addition, we use a collection 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 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 represent the default premium (DP). Finally, 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 risk reversal (RR) because it is an option-based measure for which the price is already derived from the volatility of the underlying assets. Moreover, we do not estimate the VaR of the economic sentiment (ES), as the procedure does not seem appropriate for an indicator that is not based on market data. We control for multicollinearity between the explanatory variables using the variance inflation factor (VIF). We find that explanatory variables have a VIF of 1.8 on average, with the highest VIF for $\Delta\widehat{VaR}_{DP}$ and $\Delta\widehat{VaR}_{MKT}$ (3.7 and 3.2, respectively).

3. Empirical results

3.1. Individual exposures of financial institutions to tail climate risks

In this section, we examine the first-round effect of climate risks on financial institutions based on 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.[15] Second, we examine the dynamic exposure of financial institutions to climate risks to determine whether the risk exposures have increased over time. Third, we run a variance decomposition of individual exposures to tail climate risks to better understand the sources of variation in our measure, both in time series and cross-sectional dimensions.

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

3.1.1. *Static estimation*

Figure A.2 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. 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 most European countries, although it is most pronounced in Denmark, Finland, France, Ireland, Romania, Sweden, and the UK (see Figure A.3). In contrast, the exposures of financial institutions to physical risk have a more balanced distribution, albeit with a slight leftward skew, suggesting that investors do not generally evaluate physical hazards as a tail risk for financial institutions. Negative exposures can be explained by the fact that some financial institutions face increased demand after natural disasters (e.g., Cortés and Strahan, 2017; Shelor et al., 1992). This trend is visible for all types of financial institutions (see Figure A.2). Nevertheless, a few Eastern European countries are exceptions: Greece, Romania, Hungary, and Lithuania (see Figure A.3).

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 Figure A.4, Panels 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 A.5), we show that transition risk exposure has mostly increased for banks and life and nonlife insurance companies, with the mean-group coefficient becoming significant after 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 may 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 A.6), none of the financial industries shows a significant positive exposure, but there is still an upward trend, with the coefficient for most industries becoming nonsignificantly positive by the end of the period, with the exception of REIS. Next, we examine the dynamics of climate risk exposures in the nine countries most represented in our sample of financial institutions. With regard to transition risks, we observe upward trends in France, Germany, Italy, Norway and the UK, although the coefficients are not significantly positive at the end of the period in Germany and Italy (see Figure A.7). With regard to physical risks, we observe positive trends in France, Italy, Norway, and the UK (see Figure A.8). However, only in Norway and the UK are the coefficients positive and significant in 2022. These results indicate that there is considerable heterogeneity in exposure to climate risk at country level.

3.1.3. Variance decomposition of tail climate risk indicators

To get a better understanding of the sources of variation in our climate risk indicators, we conduct a variance decomposition in Table A.3. More precisely, we regress our indicators on a set of fixed effects. By adding one type of fixed effect at a time, we can gauge the incremental explanatory power of a given type of fixed effect. We start with our transition risk indicator in column (1). We find that year fixed effects explain 1.20% of the variations of our transition risk indicators. The additional explanatory power of industry (country) fixed effects is 2.75% (5.84%). Then, industry-year and country-year fixed effects are added. They contribute to explaining an additional 0.93% and 6.38% of the variance, respectively. Finally, institution fixed effects capture 37.50% of the variance. After including all these fixed effects, 54.60% of the variations are explained. The importance of the country and country-year dimensions could be mechanically due to the presence of countries with few financial institutions. In column (2), we restrict our analysis to countries with more than 100 institution-year observations and still find that country and country-year fixed effects have comparatively more explanatory power than sector and sector-year fixed effects. We then focus on physical risk in column (3). Our results indicate that institution fixed effects incrementally explain 36.71% of the variations in physical risk exposure, while country and country-year fixed effects account for 10.88% and 10.18%, respectively. Altogether, the fixed effects explain 61.15% of the variations in the physical risk indicator. After restricting the sample to countries with more than 100 observations, the results are qualitatively similar, see column (4).

Overall, fixed effects can explain 54.60% to 61.15% of the variations in climate risk exposures. Institution, country, and country-year fixed effects have a superior explanatory power, compared to year, sector, and sector-year fixed effects. Country fixed effects are especially important in explaining changes in physical risk exposures. In addition, a significant part of the variations occurs at the institution-year level and therefore cannot be captured by fixed effects.

3.2. The effect of tail climate risks on systemic risk

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

3.2.1. Time series regressions

Using time series regressions, we examine in Table A.4 whether climate risks significantly contribute to tail risk dependence among financial institutions after considering several factors known to be predictors of systemic risk. 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 approximately 0.06 standard deviations in systemic risk.[16] 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). In addition to 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.

[16] 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.

Alternatively, in Table OA.8 (Online Appendix), 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.[17] With this alternative set of factors, 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. In 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) and other estimation methods (see Table OA.4). 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.

3.2.2. Cross-sectional regressions

Next, we conduct a cross-sectional analysis in Table A.5 to check whether the financial institutions most exposed to climate risks (according to the values of $\hat{\beta}_{BMG}$ and $\hat{\beta}_{VMS}$) contribute more to the tail dependence in the financial sector ($\hat{X}_1$), after controlling for the exposures to other risk factors. 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. As in section 3.2.1, we show that a one-standard-deviation increase in the exposure to the transition risk factor leads to an increase of around 0.06 standard deviations in the contribution of financial institutions to global risk. Therefore, the second-

[17] The analysis period is slightly shorter as these factors are available until the end of 2021 only.

round effect of transition climate risks on the financial sector appears moderate but not negligible.

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 for 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 the cross-sectional regressions, as illustrated by the effect of ML, the interbank market liquidity indicator, which appears significant only in the cross-sectional regressions. This discrepancy indicates that the two-pass regression procedure is useful to ensure the robustness of the results.

Based on the alternative set of factors, we confirm in Table OA.9 (Online Appendix) 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 10). In contrast, the coefficients associated with physical risk do not exhibit a consistent pattern. In addition, we find positive and significant effects associated with exposure to MKT, ME, ROE, EG, LIQ, QMJ, and YC. 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. In contrast, physical risks do not yet seem to have an impact on systemic risk. This conclusion remains unchanged when we estimate standard errors using a bootstrapping approach (see Table OA.5) and we substitute the baseline versions of the climate risk factors with the alternatives described in Section 2.2.[18]

3.3. Individual characteristics of financial institutions and tail climate risks

In this section, we investigate which institution-level characteristics are associated with exposure to tail climate risks. We report our results in Table A.6 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, debt, and equity market beta. Our results, reported in column (1), indicate that market capitalization, profitability, debt, 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.[19] In 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 effects. Our results confirm that larger and more indebted financial institutions tend to be more exposed to transition risks.

Next, we augment our regressions with additional extra financial characteristics, and we assess their association with transition risk exposure after controlling for year- and institution-

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[18] Contrary to GHG 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 may affect our findings on physical risk (see Section 2.2).

[19] 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.

level fixed effects. We first investigate the impact of Scope 3 GHG emissions (GHG emissions indirectly emitted by financial institutions, primarily through their investment and loan portfolios, divided by their revenue in million dollars).[20] We find that Scope 3 emission intensity is negatively associated with exposure 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.[21] Next, 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 may be explained by the fact that institutional investors tend to have long-term portfolios, and therefore, the long-term considerations of institutional owners may increase portfolio firms' awareness of long-term issues such as climate risks (see Dyck et al., 2019 and Chen et al., 2020 in the case of CSR activities). Finally, we find that greater environmental transparency is associated with lower transition risk exposure, although the effect is statistically insignificant (column 9).

[20] 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.

[21] 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."*

In Table A.7, 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 to 3). 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 that of 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 nonsignificant. Greater environmental transparency is significantly associated with lower physical risk exposure (column 6).

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 and a higher level of institutional ownership and when they are committed to addressing long-term issues.

3.4. Country-level characteristics and tail climate risks

In Section 3.1, we highlight that the variance of our climate risk indicators is primarily explained by firm-level and country-level factors. After investigating the firm-level characteristics correlating with our climate risk indicators in Section 3.3, we focus on country-level characteristics and regulatory shocks in this section.

3.4.1. Country-level climate risk

We start by assessing to which extent our institution-level indicators are correlated with country-level climate risk measures. In Table A.8, we use several proxies of country-level transition risk. To do so, we leverage data from Our World in Data (University of Oxford) and the OECD data platform (Organization for Economic Cooperation and Development). We find that transition risk is lower for institutions from countries with higher renewable energy usage (column 1), low greenhouse gas emissions (column 2), and low greenhouse gas emissions per capita (column 3). In addition, transition risk is positively correlated with the natural logarithm of country-level greenhouse gas emissions (column 4). Next, in Table A.9, we redo this exercise for physical risk, using country-level indicators of physical climate risk from the Notre Dame Global Adaptation Initiative (ND-GAIN). Our results indicate that, all else equal, physical risk is heightened for institutions from countries with high flood risk caused by climate change (column 1), high adverse impact of climate change on life expectancy (column 2), and higher dependency on foreign countries for water resources (column 3).

3.4.2. Country-level regulatory shocks

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

Our institution-level climate risk indicators reflect investors' assessment of climate risks. To the extent that ESG disclosure mandates can increase the availability of climate-related information, we expect that our climate risk indicators may be sensitive to the implementation of such mandates. We do not have strong priors on the direction of the effect: on aggregate, the additional information becoming available after the ESG mandates could lead investors to revise their risk assessment upward or downward. We start by analyzing transition risk in Panel A. In column (1), we find that the implementation of ESG mandates has a negative but insignificant effect on institutions' transition risk exposure, after controlling for country, industry, and year fixed effects.[22] We then decompose the sample into two subsamples, based on the initial value of the dynamic transition risk exposure (i.e., the value in 2014). When decomposing, we find that ESG mandates decrease the transition risk of institutions with above-median initial exposure (column 2), while it has no impact on the institutions with below-median initial exposure (column 3). The difference between the coefficients in the two subsamples is statistically significant at the 10%-level. Adding institution fixed effects yields qualitatively similar results (columns 4 to 6). This suggests that increased transparency can help the most exposed institutions to reduce their transition risk. We then focus on physical risk in Panel B. Our results indicate that exposure to physical risk is on aggregate lower after the implementation of ESG mandates, after including country, industry, and year fixed effects (column 1). When decomposing, we find that both institutions with above-median and below-median initial exposure see a decrease in their physical risk after ESG mandate implementations, even if the effect is only statistically significant for the former subgroup (columns 2 and 3). These results are confirmed after including institution fixed effects (columns 4 to 6). This suggests that informational gaps may be particularly strong in the case of physical risk, as increased transparency mitigates physical risk, regardless of the initial level of exposure.

While all the institutions in our sample are European, not all of them are from the European Union. For this reason, we can rely on another regulatory shock, namely the European Union's net-zero transition plan. As the name indicates, this shock is primarily relevant to transition risk. This plan, announced in 2019 and enforced in 2020, aims to make the European Union climate-neutral (i.e., have zero greenhouse gas emissions, in net terms) by 2050. This plan may

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

put additional pressure on financial institutions to increase their decarbonization efforts. We therefore introduce two dummy variables. The first variable, $European\,Union$, is a dummy variable equal to one if the institution is from the European Union, zero otherwise. The second variable, $Post2019$, is a dummy variable equal to one after 2019, zero otherwise. In this difference-in-differences setting, we are interested in gauging whether institutions from the European Union have become less exposed to transition risk after the implementation of the net-zero transition plan. Therefore, our interpretation focuses on the coefficient of the interaction term $EuropeanUnion * Post2019$. The results are reported in Table A.11. In column (1), we find that institutions from the European Union have a lower exposure to transition risk after the implementation of the net-zero plan. The specification includes country, industry, and year fixed effects.[23] When restricting the analysis to institutions with above-median initial transition risk exposure, we report a significant decrease in transition risk after the implementation of the net-zero plan (column 2). On the contrary, there is no discernable impact for institutions starting from a below-median transition risk (column 3). The difference in coefficients between the two subsamples is statistically significant at the 5%-level. The results are qualitatively unchanged when adding firm fixed effects (columns 4 to 6). These findings suggest that regulatory transition plans, by spurring financial institutions' decarbonization efforts, can help decrease transition risk exposure.

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

[23] The coefficient on the variable *EuropeanUnion* is omitted because country fixed effects subsume it.

regulatory shocks for climate risk mitigation, as well as additional validation exercises of our climate risk indicators.

3.5. Tail climate risk and adaptation measures

According to previous results, tail climate risks influence systemic risk within the financial sector and affect more strongly financial institutions that exhibit specific financial and extra-financial characteristics. In this section, we investigate whether financial institutions take action to adapt to tail climate risks. Our results are reported in Table A.12.

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

In column (1), we start by analyzing the Management Discussion and Analysis (MD&A) section, providing managers' key comments on the annual reports. The MD&A section is seen as allowing communication in a flexible manner (Brown, Hinson, and Tucker, 2021). We assess whether higher transition risk increases the probability of integrating ESG information in the MD&A section after controlling for the natural logarithm of market capitalization, net income, market-to-book, cash, beta, debt, environmental disclosure score, and industry-year and country-year fixed effects.[24] All our control variables are lagged by one year to mitigate

[24] 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

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 other potential 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 of disclosing ESG and climate information in the MD&A section. In unreported tests, we control for ESG disclosure score instead of environmental disclosure score. This allows us to increase our sample size, and our results are qualitatively identical. Overall, these results indicate that transition risks lead managers to disclose information through the MD&A section, a flexible communication channel, which might allow them to pursue a strategy of selective disclosure. In column (3), we further find that all else being 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 try to decrease their transition risk exposure by lowering their net GHG emissions through carbon offsetting. One caveat of this test is that our measure does not distinguish between the various types of carbon offsetting. Nonetheless, we can reasonably expect that these carbon offsets primarily pertain to Scope 3 emissions, as Scope 3 emissions represent the vast majority of financial institutions' GHG emissions.[25] Finally, we find in column (4) 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 regulators can be captured by the riskiest financial institutions. In

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).

[25] 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.

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.

Since physical risk does not appear 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 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' proactive climate risk management initiatives. We analyze the impact of physical risk on the creation of an internal team of environmental specialists (column 1), the launching of environmental products (column 2), and the use of climate scenario analysis (column 3). Our results indicate that a one-standard-deviation increase in physical risk leads to a 3.3 to 4.8 percentage point increase in the probability of engaging in such initiatives. We also find that financial institutions with higher exposure to physical risk are more likely to engage with their suppliers on climate change issues (column 4). Contrary to nonfinancial disclosure readily available to investors or an immediate lowering of net GHG emissions through offsetting, these internal initiatives create a structure that might have effects only in the long run. This differentiated response might stem from the fact that investors consider transition risks to be 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 A.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 financial institutions' disclosure strategy and their propensity to engage in various initiatives to mitigate the future effects of climate risks on their activities.

4. Conclusion

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

In addition, our results show that climate risk exposure is lower for financial institutions committed to environmental risk management, as well as and for those with more transparency and long-term orientation. Some of the recent ESG regulations seem to decrease risk levels too. We also highlight that financial institutions with cleaner investment and lending portfolios tend to be less exposed to transition risks. In summary, 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 contend that the characteristics we find associated with exposure to climate risks hold relevance for the development of both microprudential and macroprudential climate risk regulations.

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

Figure A.1

Time variations in systemic risk.

The indicator represents the first principal component $\widehat{\Omega}_1$, extracted from Equations (2) and (3), and it accounts for the common variations in the VaR of financial institutions. The chart on the left represents the systemic risk indicator used in Equation (10), while the chart on the right is in levels (January 2005 = 100).

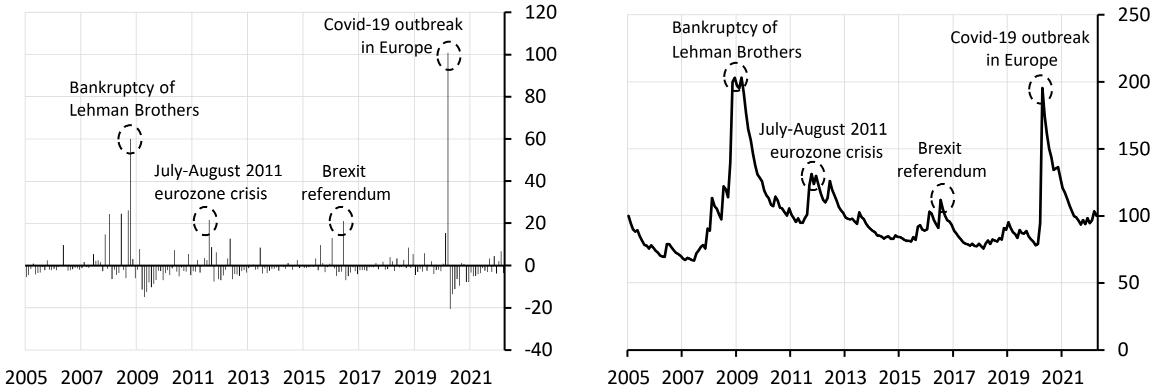


Figure A.2

Distribution of climate risk exposures by type of financial institution.

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. The left panel provides details by type of financial institution for $\hat{\beta}_{BMG}$, the transition risk exposure indicator. The right panel provides details by type of financial institution for $\hat{\beta}_{VMS}$, the physical risk exposure indicator. The acronyms REIT and REIS stand for "real estate investment trusts" and "real estate investment services", respectively.

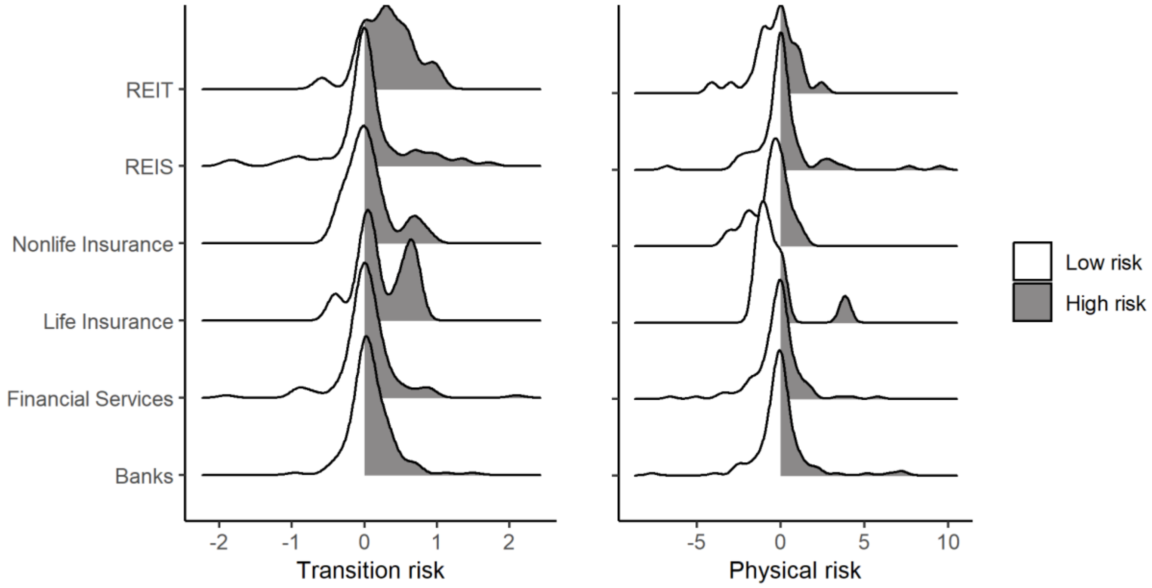


Figure A.3

Climate risk exposures by country.

The map represents the geographical distribution of financial institutions' exposures to climate risks, $\hat{\beta}_{BMG}$ and $\hat{\beta}_{VMS}$, estimated in Equation (6). The left-hand panel provides details by country for $\hat{\beta}_{BMG}$, the transition risk exposure indicator. The right-hand panel provides details by country for $\hat{\beta}_{VMS}$, the physical risk exposure indicator. For each country, we calculate the weighted average of the climate risk exposure coefficients of national financial institutions. The weights are based on the average market value of each financial institution over the period 2005-2022.

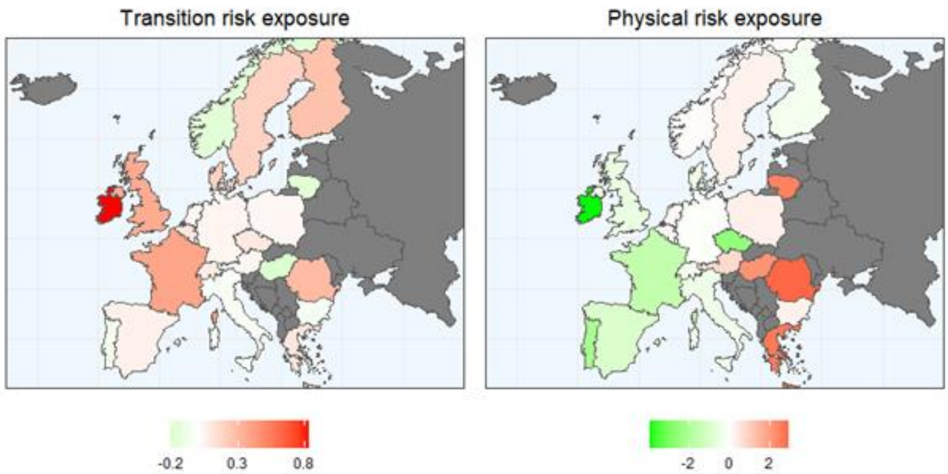
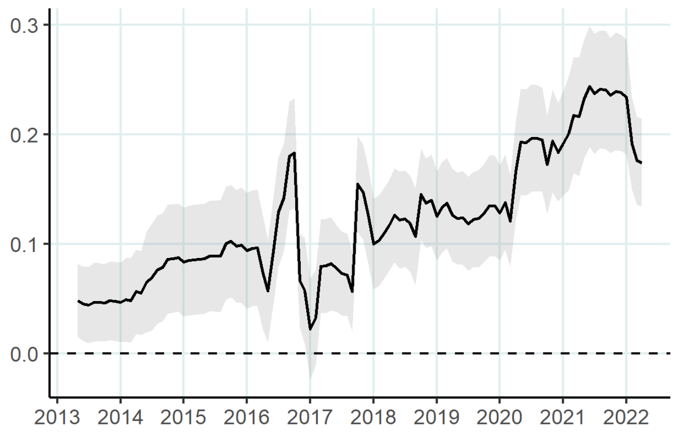


Figure A.4

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

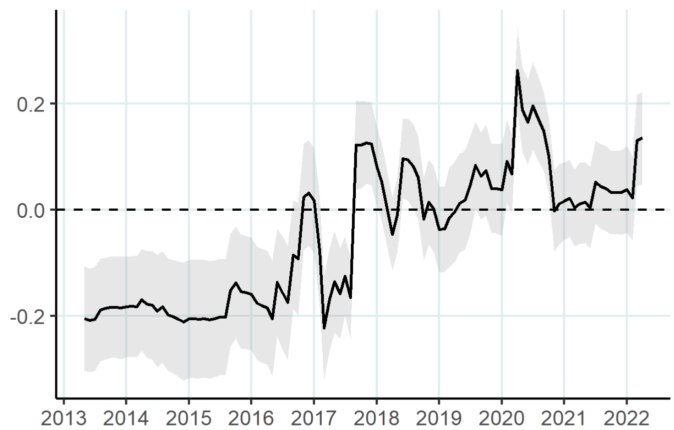


Figure A.5

Dynamic transition risk exposures by type of financial institution

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.

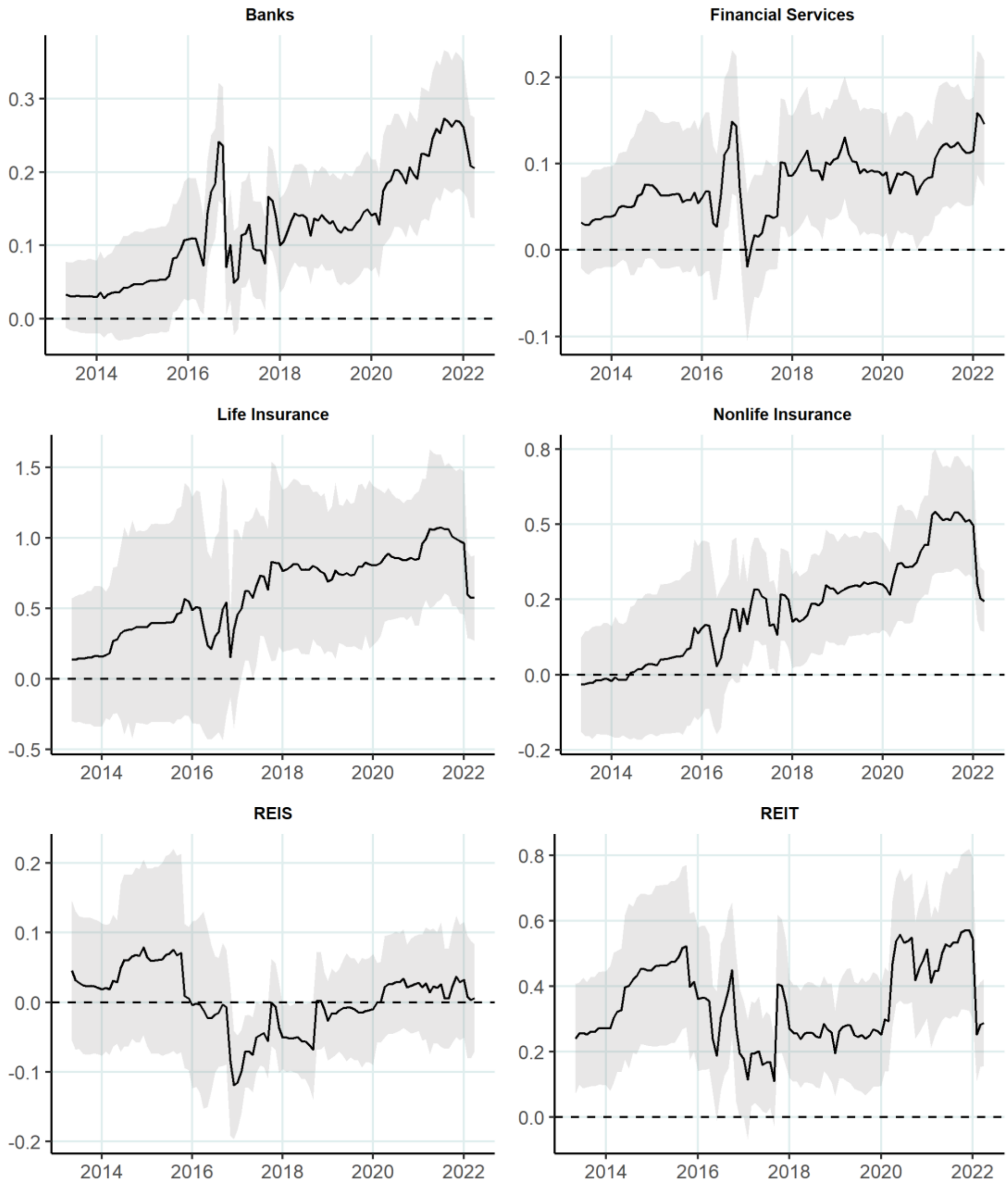


Figure A.6

Dynamic physical risk exposures by type of financial institution

The figure represents the average dynamics 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.

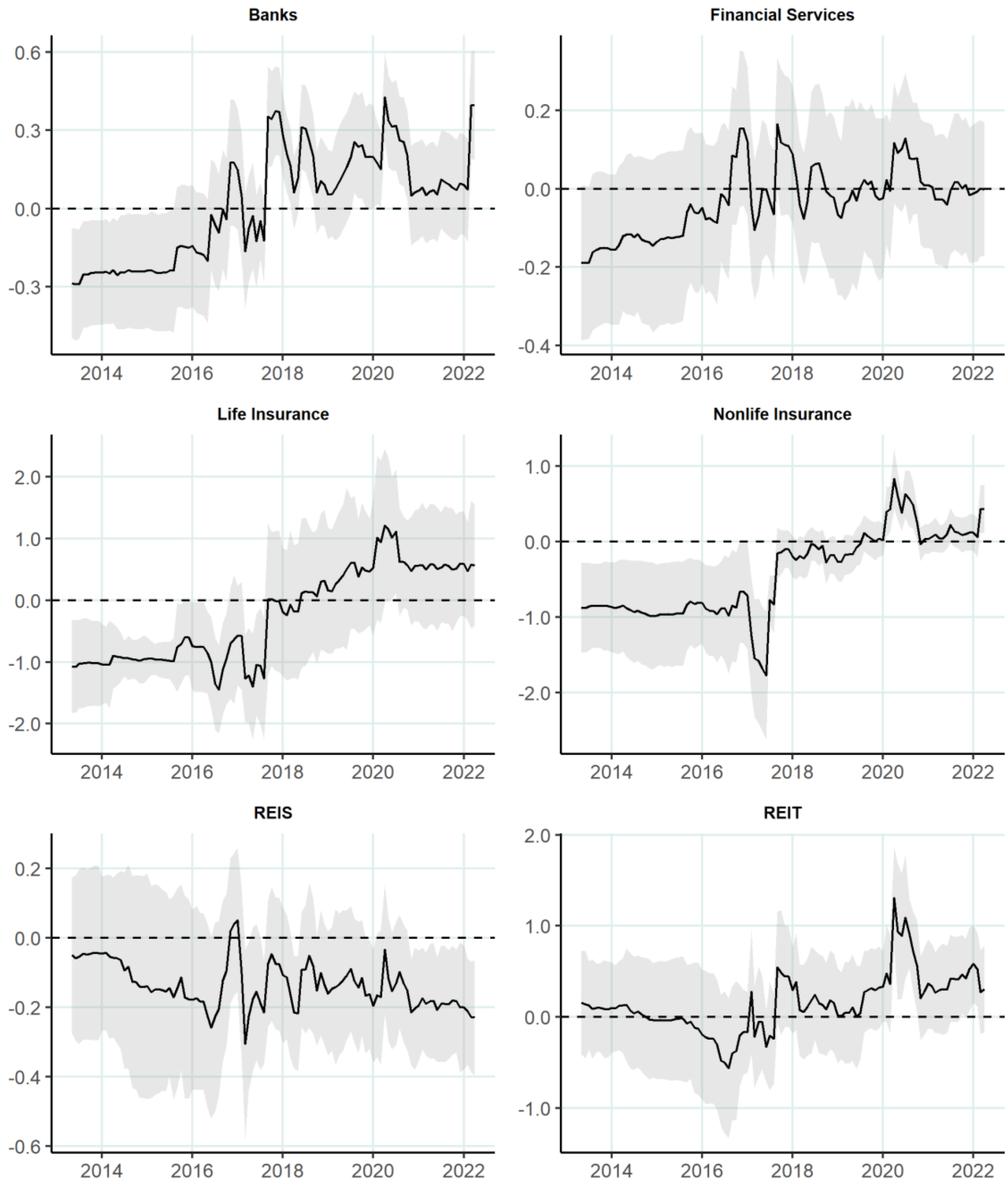


Figure A.7

Dynamic transition risk exposures by country

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 the nine countries most represented in our sample of financial institutions.

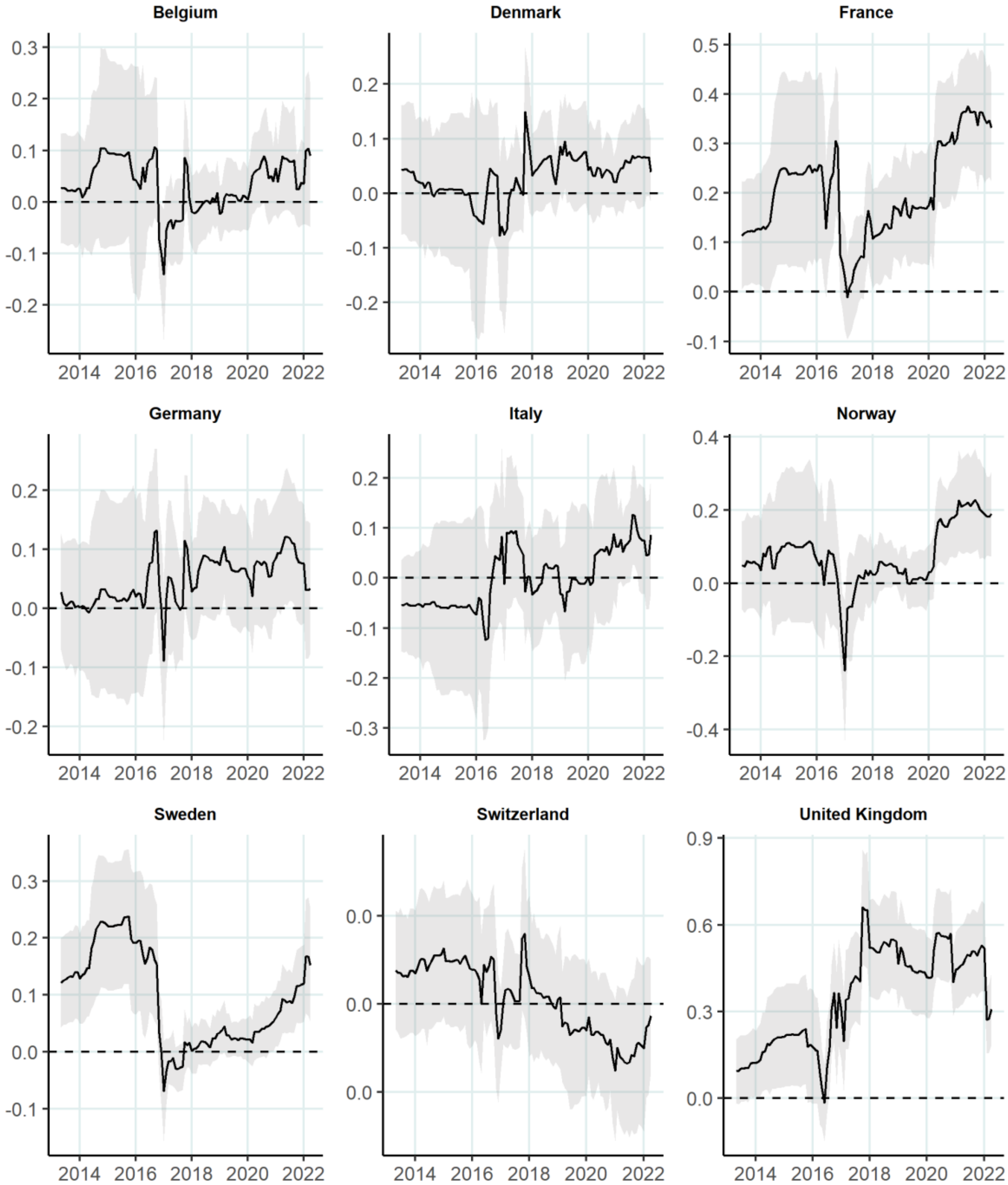


Figure A.8

Dynamic physical risk exposures by country

The figure represents the average dynamics 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 the nine countries most represented in our sample of financial institutions.

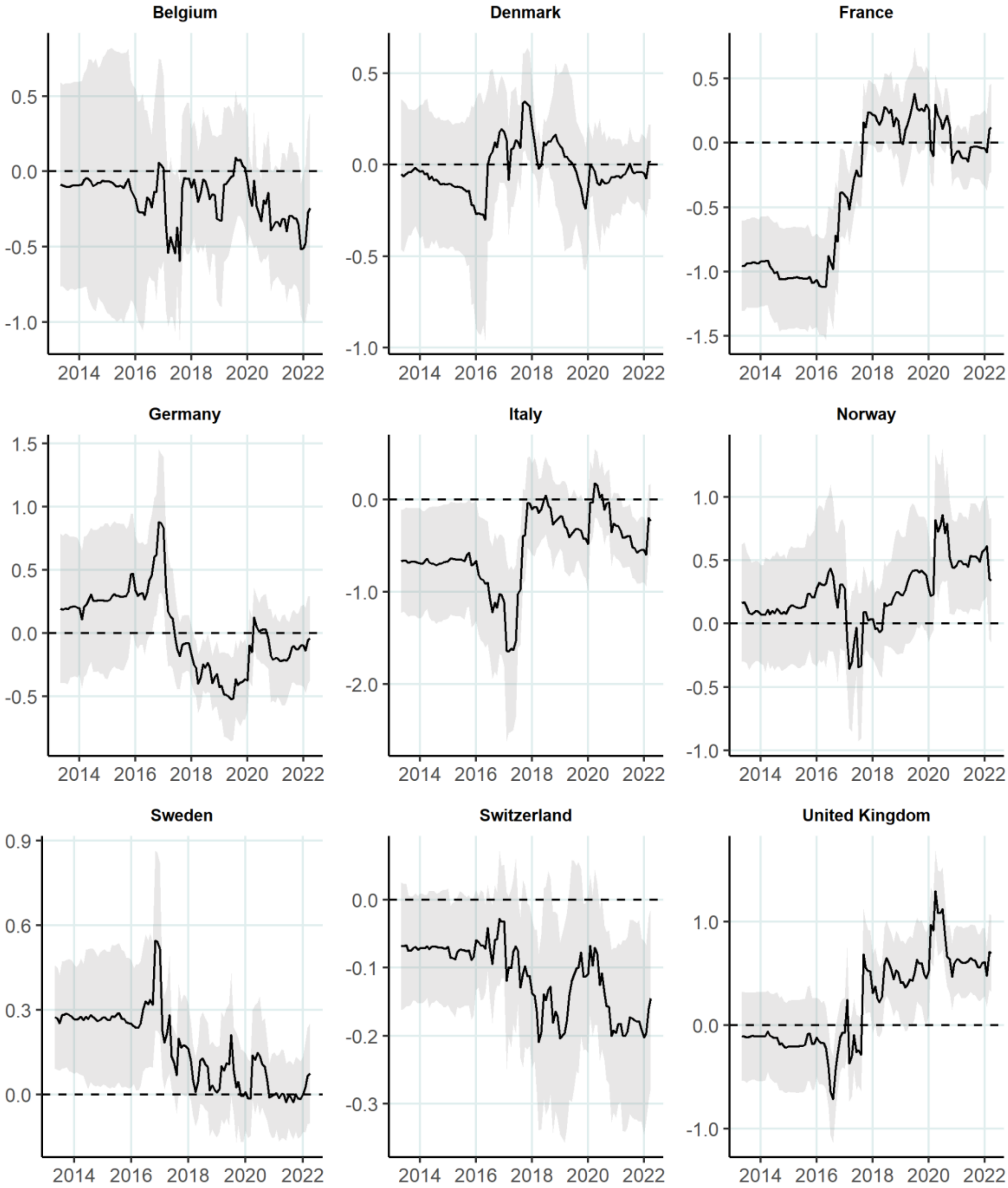


Table A.1

Correlation matrix for risk factors.

This table presents the correlation matrix among the $\Delta\widehat{VaR}$ 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 A.2

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.

VARIABLES	N	Mean	SD	Median	P25	P75
$\hat{\beta}_{BMG_{i,avg}}$	6,350	0.081	0.385	0.025	-0.072	0.222
$\hat{\beta}_{VMS_{i,avg}}$	6,350	-0.120	1.564	-0.034	-0.664	0.251
$\hat{\beta}_{BMG_{i,t}}$	3,321	0.154	0.719	0.028	-0.098	0.391
$\hat{\beta}_{VMS_{i,t}}$	3,321	0.069	1.958	-0.012	-0.601	0.504
Beta	6,350	0.824	0.559	0.760	0.392	1.175
LogMarketValue	6,350	6.454	2.128	6.395	4.836	7.918
Cash	6,350	0.046	0.092	0.006	0.000	0.047
NetIncome	6,350	0.023	0.070	0.010	0.003	0.041
MtoB	6,350	1.276	1.192	0.972	0.629	1.479
Debt	6,635	45.242	30.809	45.960	17.160	75.030
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
Environmental Transparency Score	991	0.187	0.204	0.130	0.06	0.27
IntegratedStrategy	6,415	0.083	0.275	0.000	0.000	0.000
DiscussClimateRisk	2,621	0.253	0.435	0.000	0.000	1.000
LogCarbonOffsets	524	9.558	2.614	9.349	7.881	11.299
PolicyEngagement	1,700	0.747	0.435	1.000	0.000	1.000
EnvironmentalTeam	6,350	0.166	0.372	0.000	0.000	0.000
EnvironmentalProducts	2,596	0.457	0.498	0.000	0.000	1.000
ClimateScenarioAnalysis	1,218	0.201	0.401	0.000	0.000	0.000
SupplierClimateEngagement	800	0.928	0.259	1.000	1.000	1.000

Table A.3

Variance decomposition

This table presents a variance decomposition of the tail climate risk indicators. The following equation is estimated: $Climate\ risk_{i,t} = \alpha + \beta X_{i,t} + \varepsilon_{i,t}$. Columns (1) and (2) use $\hat{\beta}_{BMG}$, our measure of tail transition risk, as the dependent variable. Columns (3) and (4) use $\hat{\beta}_{VMS}$, our measure of tail physical risk, as the dependent variable. $\hat{\beta}_{BMG}$ and $\hat{\beta}_{VMS}$ are estimated dynamically on a rolling window of 100 observations from Equation (6). $X_{i,t}$ is a vector of fixed effects. $\varepsilon_{i,t}$ is the error term. For each line of the table, the information in bold represents the fixed effect that is added compared to the previous line, and its incremental R² is reported in italics. Columns (1) and (3) use the total sample. Columns (2) and (4) restrict the sample to countries with more than 100 institution-year observations.

FIXED EFFECTS	(1) $\hat{\beta}_{BMG_{i,t}}$	(2) $\hat{\beta}_{BMG_{i,t}}$	(3) $\hat{\beta}_{VMS_{i,t}}$	(4) $\hat{\beta}_{VMS_{i,t}}$
	Total sample	Only countries with more than 100 observations	Total sample	Only countries with more than 100 observations
Year	*1.20%*	*1.25%*	*0.91%*	*0.85%*
Year, **Industry**	*2.75%*	*2.65%*	*1.21%*	*1.37%*
Year, Industry, **Country**	*5.84%*	*4.95%*	*10.88%*	*9.12%*
Country, **Industry-Year**	*0.93%*	*1.13%*	*1.26%*	*1.49%*
Industry-Year, **Country-Year**	*6.38%*	*4.38%*	*10.18%*	*8.14%*
Industry-Year, Country-Year, **Institution**	*37.50%*	*44.38%*	*36.71%*	*39.19%*
Total explained by fixed effects	54.60%	58.74%	61.15%	60.16%
Total explained by firm variations	45.40%	41.26%	38.85%	39.84%

Table A.4

Determinants of systemic risk – time series dimension

This table presents the determinants of systemic risk based on the time series analysis described in Equation (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 $\widehat{\Delta VaR}$ 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.

VARIABLES	(1) $\widehat{\Omega}_1$	(2) $\widehat{\Omega}_1$	(3) $\widehat{\Omega}_1$	(4) $\widehat{\Omega}_1$
BMG	1.275** (0.541)	0.788* (0.478)	1.135* (0.638)	0.701* (0.413)
VMS	-0.033 (1.750)	-1.205 (1.875)	1.086 (1.594)	-0.868 (1.459)
MKT	3.276*** (0.374)	3.183*** (0.423)		1.948*** (0.466)
SMB	11.441*** (3.297)	11.274*** (3.221)		5.498*** (1.910)
HML	6.061*** (1.592)	5.951*** (1.819)		2.096* (1.172)
RMW		-0.892 (3.374)		3.369 (2.485)
CMA		0.295 (0.555)		0.129 (0.469)
WML		0.616*** (0.227)		0.469*** (0.180)
ML			6.861 (8.634)	-0.104 (8.037)
DP			7.089*** (0.939)	2.357** (0.921)
YC			-0.190 (0.511)	0.463 (0.638)
NS			3.360*** (0.946)	1.562 (1.125)
RR			-1.429** (0.665)	-0.455 (0.428)
ES			1.657*** (0.165)	1.186*** (0.183)
Constant	-0.054 (0.306)	-0.060 (0.296)	-0.058 (0.282)	-0.052 (0.230)
Observations	207	207	207	207
R-squared	0.820	0.829	0.831	0.899
Adjusted R-squared	0.816	0.822	0.824	0.892

Table A.5

Determinants of systemic risk – cross-sectional dimension

This table presents the cross-sectional analysis, as described in Equation (11). 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). White heteroskedasticity-robust standard errors are reported in parentheses in columns (1) to (4). We include industry and country fixed effects and report clustered standard errors at the country level in columns (5) to (8).

VARIABLES	(1) $\hat{X}_1$	(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*** (0.004)	0.012*** (0.004)	0.007** (0.003)	0.007** (0.003)	0.010*** (0.003)	0.012** (0.005)	0.006* (0.003)	0.008*** (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)	0.002* (0.001)
$\hat{\beta}_{MKT}$	0.013*** (0.004)	0.011*** (0.004)		0.026*** (0.004)	0.011 (0.013)	0.009 (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*** (0.002)	0.005** (0.002)		0.007*** (0.002)	0.002 (0.002)	0.004 (0.006)		0.004 (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 (0.013)		0.005 (0.004)
$\hat{\beta}_{WML}$		0.030*** (0.009)		0.010 (0.006)		0.017 (0.011)		0.005 (0.013)
$\hat{\beta}_{ML}$			0.0002** (0.0001)	0.0005*** (0.0001)			0.0001 (0.0001)	0.0003** (0.0001)
$\hat{\beta}_{DP}$			0.003*** (0.001)	0.007*** (0.001)			0.005*** (0.001)	0.007*** (0.002)
$\hat{\beta}_{YC}$			0.0003 (0.002)	-0.002 (0.002)			0.001 (0.002)	-0.002 (0.003)
$\hat{\beta}_{NS}$			0.002*** (0.001)	-0.003*** (0.001)			0.001*** (0.0003)	-0.004*** (0.001)
$\hat{\beta}_{RR}$			0.003 (0.002)	-0.006** (0.003)			-0.001 (0.002)	-0.009** (0.004)
$\hat{\beta}_{ES}$			0.073*** (0.008)	0.053*** (0.007)			0.063*** (0.015)	0.051*** (0.014)
Constant	0.026*** (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	0.140	0.171	0.251	0.377	0.306	0.318	0.404	0.478
Adjusted R-squared	0.128	0.152	0.234	0.352	0.236	0.242	0.338	0.409
Country Fixed Effects	No	No	No	No	Yes	Yes	Yes	Yes
Industry Fixed Effects	No	No	No	No	Yes	Yes	Yes	Yes

Table A.6

Tail transition risk and characteristics of financial institutions.

This table presents the characteristics associated with financial institutions' exposures to climate transition risks, $\hat{\beta}_{BMG}$, estimated from Equation (6). In columns (1) and (2), $\hat{\beta}_{BMG}$ is estimated statically, and heteroskedasticity-robust standard errors are reported in parentheses. In columns (3) to (9), $\hat{\beta}_{BMG}$ 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 (9) use institution and year fixed effects. Appendix B presents variable definitions. ***, **, and * indicate significance at the 1%, 5% and 10% levels, respectively.

VARIABLES	(1) $\hat{\beta}_{BMG_{i,avg}}$	(2) $\hat{\beta}_{BMG_{i,avg}}$	(3) $\hat{\beta}_{BMG_{i,t}}$	(4) $\hat{\beta}_{BMG_{i,t}}$	(5) $\hat{\beta}_{BMG_{i,t}}$	(6) $\hat{\beta}_{BMG_{i,t}}$	(7) $\hat{\beta}_{BMG_{i,t}}$	(8) $\hat{\beta}_{BMG_{i,t}}$	(9) $\hat{\beta}_{BMG_{i,t}}$
Beta (t-1)	0.0442***	0.0209*	-0.00897	-0.239	-0.430*	-0.436**	-0.0959	-0.0915	-0.342**
	(0.0113)	(0.0112)	(0.0710)	(0.225)	(0.225)	(0.181)	(0.0972)	(0.0843)	(0.152)
LogMarketValue (t-1)	0.0218***	0.0228***	0.0698***	0.172	-0.0534	0.0148	0.0336	-0.0214	0.0597
	(0.00267)	(0.00277)	(0.0162)	(0.174)	(0.184)	(0.205)	(0.0763)	(0.0658)	(0.157)
Cash (t-1)	-0.196***	-0.168***	-0.0799	0.146	0.0855	-0.363	-0.129	0.119	0.0461
	(0.0588)	(0.0627)	(0.232)	(0.802)	(1.177)	(0.832)	(0.329)	(0.344)	(0.693)
NetIncome (t-1)	0.318***	0.237***	0.0245	-1.125	-1.359	-0.157	-0.189	0.102	-0.0960
	(0.0922)	(0.0907)	(0.249)	(0.804)	(1.066)	(0.857)	(0.244)	(0.227)	(0.594)
MtoB (t-1)	0.00765*	0.00284	-0.0438**	0.0126	0.367**	0.250	-0.0371	-0.0572	0.190
	(0.00452)	(0.00443)	(0.0210)	(0.102)	(0.149)	(0.170)	(0.0395)	(0.0504)	(0.132)
Debt (t-1)	0.000646***	0.00120***	0.00257**	0.00224	0.00236	0.00931	0.00203	-0.000340	0.00622
	(0.000176)	(0.000231)	(0.00125)	(0.00676)	(0.00600)	(0.00638)	(0.00285)	(0.00268)	(0.00422)
LowScope3intensity (t-1)				-0.118*					
				(0.0712)					
VerifiedScope3 (t-1)					-0.298*				
					(0.152)				
ReductionTargetReached (t-1)						-0.148**			
						(0.0705)			
Board LT incentives (t-1)							-0.0720*		
							(0.0408)		
Institutional ownership (t-1)								-0.362***	
								(0.114)	
Environmental Transparency Score (t-1)									-0.485
									(0.308)
Constant	-0.133***	-0.321***	-0.394*	-0.650	1.248	0.250	0.129	0.684	0.0319
	(0.0190)	(0.0770)	(0.212)	(1.625)	(1.697)	(1.722)	(0.547)	(0.468)	(1.302)
Observations	5,992	5,992	3,245	872	715	699	3,245	2,222	879
R-squared	0.038	0.166	0.139	0.677	0.632	0.719	0.542	0.706	0.695
Adjusted R-squared	0.037	0.161	0.128	0.600	0.575	0.647	0.482	0.649	0.638
Country Fixed Effects	No	Yes	Yes						
Industry Fixed Effects	No	Yes	Yes						
Institution Fixed Effects	No	No	No	Yes	Yes	Yes	Yes	Yes	Yes
Year Fixed Effects	No	No	Yes	Yes	Yes	Yes	Yes	Yes	Yes

Table A.7

Tail physical risk and characteristics of financial institutions.

This table presents the characteristics associated with financial institutions' 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 (6), $\hat{\beta}_{VMS}$ 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), (5), and (6) use institution and year fixed effects. Appendix B presents variable definitions. ***, **, and * indicate significance at the 1%, 5% and 10% levels, respectively.

VARIABLES	(1) $\hat{\beta}_{VMS_{i,avg}}$	(2) $\hat{\beta}_{VMS_{i,avg}}$	(3) $\hat{\beta}_{VMS_{i,t}}$	(4) $\hat{\beta}_{VMS_{i,t}}$	(5) $\hat{\beta}_{VMS_{i,t}}$	(6) $\hat{\beta}_{VMS_{i,t}}$
Beta (t-1)	0.301***	0.325***	0.434*	0.0970	-0.401	0.00212
	(0.0537)	(0.0494)	(0.224)	(0.320)	(0.292)	(0.546)
LogMarketValue (t-1)	-0.102***	-0.0565***	-0.0520	-0.440**	-0.412*	-1.117***
	(0.0109)	(0.0113)	(0.0444)	(0.189)	(0.223)	(0.345)
Cash (t-1)	-0.0436	0.570**	-0.0540	-0.0931	0.790	-2.262
	(0.199)	(0.223)	(0.563)	(0.534)	(0.559)	(4.512)
NetIncome (t-1)	0.568*	0.505	0.181	0.268	-0.144	1.692
	(0.325)	(0.328)	(0.741)	(0.661)	(0.812)	(2.277)
MtoB (t-1)	-0.0446**	-0.0309*	-0.0159	0.123	0.237**	0.214
	(0.0192)	(0.0178)	(0.0785)	(0.0958)	(0.103)	(0.355)
Debt (t-1)	0.00298***	0.000971	-0.000392	-0.00521	0.00741	-0.0139
	(0.000735)	(0.000855)	(0.00331)	(0.00714)	(0.00783)	(0.0185)
Board LT incentives (t-1)				-0.0180		
				(0.160)		
Institutional ownership (t-1)					-0.0811	
					(0.326)	
Environmental Transparency Score (t-1)						-2.680*
						(1.368)
Constant	0.197***	1.609***	0.617	3.189**	2.516	11.70***
	(0.0684)	(0.236)	(0.648)	(1.424)	(1.577)	(3.408)
Observations	5,992	5,992	3,245	3,245	2,222	879
R-squared	0.022	0.218	0.139	0.504	0.644	0.675
Adjusted R-squared	0.021	0.213	0.127	0.439	0.576	0.615
Country Fixed Effects	No	Yes	Yes			
Industry Fixed Effects	No	Yes	Yes			
Institution Fixed Effects	No	No	No	Yes	Yes	Yes
Year Fixed Effects	No	No	Yes	Yes	Yes	Yes

Table A.8

Country-level climate transition indicators and tail transition risk

This table presents the association between country-level transition risk indicators and financial institutions' exposures to transition climate risk, $\hat{\beta}_{BMG}$. $\hat{\beta}_{BMG}$ is estimated dynamically on a rolling window of 100 observations from Equation (6). Country-level indicators of transition climate risk are taken from Our World in Data (University of Oxford) and the OECD data platform (Organization for Economic Cooperation and Development). Column (1) uses $HighRenewables$, a dummy variable equal to one if the institution's country is in the top quartile of renewable energy usage, as country-level indicator of transition climate risk. Column (2) uses $LowEmissions$, a dummy variable equal to one if the institution's country is in the bottom quartile of greenhouse gas emissions, as country-level indicator of transition climate risk. Column (3) uses $LowEmissionsPerCapita$, a dummy variable equal to one if the institution's country is in the bottom quartile of greenhouse gas emissions per capita, as country-level indicator of transition climate risk. Column (4) uses $LogEmissions$, the natural logarithm of the institution's country greenhouse gas emissions, as country-level indicator of transition climate risk. All regressions use industry and year fixed effects. Standard errors clustered at the institution level are reported in parentheses. Appendix B presents variable definitions. ***, **, and * indicate significance at the 1%, 5% and 10% levels, respectively.

VARIABLES	(1) $\hat{\beta}_{BMG_{i,t}}$	(2) $\hat{\beta}_{BMG_{i,t}}$	(3) $\hat{\beta}_{BMG_{i,t}}$	(4) $\hat{\beta}_{BMG_{i,t}}$
Beta (t-1)	0.0214 (0.0759)	0.0215 (0.0800)	0.0337 (0.0775)	0.0329 (0.0807)
LogMarketValue (t-1)	0.0699*** (0.0168)	0.0635*** (0.0173)	0.0659*** (0.0170)	0.0629*** (0.0170)
Cash (t-1)	0.119 (0.213)	0.0334 (0.207)	0.0344 (0.206)	0.00280 (0.209)
NetIncome (t-1)	0.203 (0.249)	0.167 (0.244)	0.213 (0.244)	0.220 (0.243)
MtoB (t-1)	-0.0110 (0.0203)	-0.0159 (0.0201)	-0.0173 (0.0202)	-0.0180 (0.0202)
Debt (t-1)	0.00221* (0.00129)	0.00200 (0.00134)	0.00211 (0.00132)	0.00203 (0.00132)
HighRenewables (t-1)	-0.143*** (0.0480)			
LowEmissions (t-1)		-0.144*** (0.0498)		
LowEmissionsPerCapita (t-1)			-0.131*** (0.0469)	
LogEmissions (t-1)				0.0698*** (0.0232)
Constant	-0.506*** (0.122)	-0.462*** (0.122)	-0.330*** (0.125)	-1.350*** (0.332)
Observations	3,200	3,122	3,122	3,122
R-squared	0.089	0.084	0.083	0.088
Adjusted R-squared	0.084	0.078	0.077	0.082
Industry Fixed Effects	Yes	Yes	Yes	Yes
Year Fixed Effects	Yes	Yes	Yes	Yes

Table A.9

Country-level physical risk indicators and tail physical risk

This table presents the association between country-level physical risk indicators and financial institutions' exposures to physical climate risk, $\hat{\beta}_{VMS}$. $\hat{\beta}_{VMS}$ is estimated dynamically on a rolling window of 100 observations from Equation (6). Country-level indicators of physical climate risk are taken from the Notre-Dame Global Adaptation Initiative (ND-GAIN). Column (1) uses $Floods$, the projected change in flood hazard. Column (2) uses $Deaths$, the projected loss of life years. Column (3) uses $WaterDependency$, the proportion of water resources originating from outside the country. All regressions use industry and year fixed effects. Standard errors clustered at the institution level are reported in parentheses. Appendix B presents variable definitions. ***, **, and * indicate significance at the 1%, 5% and 10% levels, respectively.

VARIABLES	(1) $\hat{\beta}_{VMS_{i,t}}$	(2) $\hat{\beta}_{VMS_{i,t}}$	(3) $\hat{\beta}_{VMS_{i,t}}$
Beta (t-1)	0.414	0.361	0.441*
	(0.256)	(0.261)	(0.263)
LogMarketValue (t-1)	-0.103**	-0.0793	-0.110**
	(0.0505)	(0.0499)	(0.0526)
Cash (t-1)	-0.0341	0.170	-0.178
	(0.553)	(0.503)	(0.546)
NetIncome (t-1)	-0.0894	0.406	0.394
	(0.749)	(0.681)	(0.718)
MtoB (t-1)	-0.0186	-0.00363	0.0170
	(0.0840)	(0.0776)	(0.0852)
Debt (t-1)	-0.00366	-0.00228	-0.00395
	(0.00315)	(0.00317)	(0.00315)
Floods (t-1)	3.208***		
	(1.067)		
Deaths (t-1)		29.09**	
		(11.61)	
WaterDependency (t-1)			0.735*
			(0.423)
Constant	-1.773**	-0.667	0.439*
	(0.828)	(0.488)	(0.254)
Observations	2,885	2,885	2,885
R-squared	0.049	0.053	0.043
Adjusted R-squared	0.043	0.046	0.037
Industry Fixed Effects	Yes	Yes	Yes
Year Fixed Effects	Yes	Yes	Yes

Table A.10

Staggered differences-in-differences in tail climate risks around ESG disclosure mandates

This table presents staggered difference-in-differences estimates for tail climate risks before and after ESG disclosure mandates. Panel A uses $\hat{\beta}_{BMG}$, our measure of tail transition risk, as the dependent variable. Panel B uses $\hat{\beta}_{VMS}$, our measure of tail physical risk , as the dependent variable. $\hat{\beta}_{BMG}$ and $\hat{\beta}_{VMS}$ are estimated dynamically on a rolling window of 100 observations from Equation (6). These dynamic indicators are available from 2014. Columns (1) to (3) use country, industry, and year fixed effects. Columns (4) to (6) use institution and year fixed effects. Regressions (1) and (4) use the total sample. Regressions (2) and (5) use the financial institutions with above median climate risk in 2014. Regressions (3) and (6) use the financial institutions with climate risk below or equal to median in 2014. Standard errors are clustered at the financial institution level and are reported in parentheses. Appendix B presents variable definitions. ***, **, and * indicate significance at the 1%, 5% and 10% levels, respectively.

Panel A: Transition risk

VARIABLES	(1) $\hat{\beta}_{BMG_{i,t}}$	(2) $\hat{\beta}_{BMG_{i,t}}$	(3) $\hat{\beta}_{BMG_{i,t}}$	(4) $\hat{\beta}_{BMG_{i,t}}$	(5) $\hat{\beta}_{BMG_{i,t}}$	(6) $\hat{\beta}_{BMG_{i,t}}$
	Total sample	Above median Transition risk	Below median Transition risk	Total sample	Above median Transition risk	Below median Transition risk
Beta (t-1)	-0.00795	-0.139	0.000577	-0.0944	-0.159	-0.0243
	(0.0709)	(0.0944)	(0.0959)	(0.0965)	(0.166)	(0.103)
LogMarketValue (t-1)	0.0697***	0.0600**	0.0796***	0.0316	-0.00202	0.0819
	(0.0162)	(0.0240)	(0.0216)	(0.0758)	(0.104)	(0.0974)
Cash (t-1)	-0.0756	-0.271	0.157	-0.123	-0.328	-0.0604
	(0.233)	(0.294)	(0.326)	(0.332)	(0.530)	(0.427)
NetIncome (t-1)	0.0350	-0.185	0.385	-0.173	-0.366	0.0399
	(0.248)	(0.321)	(0.350)	(0.243)	(0.316)	(0.333)
MtoB (t-1)	-0.0445**	-0.0699**	-0.0296	-0.0390	-0.0127	-0.0762
	(0.0211)	(0.0292)	(0.0261)	(0.0395)	(0.0520)	(0.0623)
Debt (t-1)	0.00253**	0.00299	0.00230	0.00177	0.00107	0.00243
	(0.00125)	(0.00203)	(0.00139)	(0.00283)	(0.00386)	(0.00396)
ESGmandate	-0.127*	-0.256**	0.00570	-0.128	-0.262**	0.00601
	(0.0746)	(0.105)	(0.105)	(0.0799)	(0.111)	(0.110)
Constant	-0.279	-0.117	-0.261	0.261	0.654	-0.242
	(0.225)	(0.313)	(0.195)	(0.568)	(0.802)	(0.656)
Observations	3,245	1,614	1,631	3,245	1,614	1,631
R-squared	0.140	0.190	0.239	0.542	0.524	0.568
Adjusted R-squared	0.129	0.168	0.219	0.482	0.459	0.509
Country Fixed Effects	Yes	Yes	Yes			
Industry Fixed Effects	Yes	Yes	Yes			
Institution FE	No	No	No	Yes	Yes	Yes
Year Fixed Effects	Yes	Yes	Yes	Yes	Yes	Yes

Panel B: Physical risk

VARIABLES	(1) $\hat{\beta}_{VMS_{i,t}}$ Total sample	(2) $\hat{\beta}_{VMS_{i,t}}$ Above median Physical risk	(3) $\hat{\beta}_{VMS_{i,t}}$ Below median Physical risk	(4) $\hat{\beta}_{VMS_{i,t}}$ Total sample	(5) $\hat{\beta}_{VMS_{i,t}}$ Above median Physical risk	(6) $\hat{\beta}_{VMS_{i,t}}$ Below median Physical risk
Beta (t-1)	0.438*	0.479	0.343	0.108	0.408	-0.153
	(0.224)	(0.332)	(0.310)	(0.321)	(0.320)	(0.551)
LogMarketValue (t-1)	-0.0523	-0.122*	0.0268	-0.450**	-0.114	-0.751**
	(0.0444)	(0.0712)	(0.0462)	(0.190)	(0.195)	(0.320)
Cash (t-1)	-0.0354	-0.205	-0.619	-0.0578	1.061*	-1.066
	(0.560)	(0.697)	(1.104)	(0.543)	(0.546)	(1.099)
NetIncome (t-1)	0.226	1.139	-0.723	0.338	0.250	0.644
	(0.748)	(0.699)	(1.222)	(0.667)	(0.621)	(1.232)
MtoB (t-1)	-0.0191	0.0307	-0.0652	0.118	-0.00923	0.274
	(0.0788)	(0.108)	(0.0686)	(0.0951)	(0.0656)	(0.192)
Debt (t-1)	-0.000565	0.00939*	-0.00940***	-0.00639	-0.000985	-0.0105
	(0.00331)	(0.00562)	(0.00329)	(0.00725)	(0.00830)	(0.0118)
ESGmandate	-0.546**	-0.711**	-0.442	-0.568**	-0.737***	-0.454
	(0.211)	(0.277)	(0.316)	(0.227)	(0.280)	(0.350)
Constant	1.109	0.476	1.259	3.793***	1.308	5.967**
	(0.709)	(0.907)	(1.049)	(1.464)	(1.397)	(2.496)
Observations	3,245	1,585	1,660	3,245	1,585	1,660
R-squared	0.142	0.186	0.182	0.508	0.597	0.446
Adjusted R-squared	0.130	0.164	0.161	0.443	0.542	0.371
Country FE	Yes	Yes	Yes			
Industry FE	Yes	Yes	Yes			
Institution FE	No	No	No	Yes	Yes	Yes
Year FE	Yes	Yes	Yes	Yes	Yes	Yes

Table A.11

Difference-in-differences in tail transition risk around European Union’s net-zero plan

This table presents difference-in-differences estimates for tail transition risk before and after 2019, using $\hat{\beta}_{BMG}$ as the dependent variable. $\hat{\beta}_{BMG}$ is estimated dynamically on a rolling window of 100 observations from Equation (6). This dynamic indicator is available from 2014. Columns (1) to (3) use country, industry, and year fixed effects. Columns (4) to (6) use institution and year fixed effects. Regressions (1) and (4) use the total sample. Regressions (2) and (5) use the financial institutions with above median transition risk in 2014. Regressions (3) and (6) use the financial institutions with transition risk below or equal to median in 2014. Standard errors are clustered at the financial institution level and are reported in parentheses. Appendix B presents variable definitions. ***, **, and * indicate significance at the 1%, 5% and 10% levels, respectively.

VARIABLES	(1) $\hat{\beta}_{BMG_{i,t}}$	(2) $\hat{\beta}_{BMG_{i,t}}$	(3) $\hat{\beta}_{BMG_{i,t}}$	(4) $\hat{\beta}_{BMG_{i,t}}$	(5) $\hat{\beta}_{BMG_{i,t}}$	(6) $\hat{\beta}_{BMG_{i,t}}$
	Total sample	Above median Transition risk	Below median Transition risk	Total sample	Above median Transition risk	Below median Transition risk
Beta (t-1)	-0.00481	-0.137	-0.00181	-0.0879	-0.151	-0.0287
	(0.0705)	(0.0937)	(0.0958)	(0.0953)	(0.163)	(0.103)
LogMarketValue (t-1)	0.0692***	0.0600**	0.0800***	0.0313	0.00474	0.0837
	(0.0162)	(0.0239)	(0.0217)	(0.0760)	(0.104)	(0.0966)
Cash (t-1)	-0.0860	-0.285	0.162	-0.146	-0.365	-0.0539
	(0.232)	(0.292)	(0.325)	(0.329)	(0.518)	(0.431)
NetIncome (t-1)	0.0416	-0.197	0.375	-0.168	-0.400	0.0255
	(0.247)	(0.320)	(0.347)	(0.241)	(0.308)	(0.335)
MtoB (t-1)	-0.0443**	-0.0695**	-0.0295	-0.0392	-0.0146	-0.0760
	(0.0211)	(0.0293)	(0.0261)	(0.0395)	(0.0507)	(0.0625)
Debt (t-1)	0.00254**	0.00295	0.00229	0.00186	0.000866	0.00242
	(0.00125)	(0.00202)	(0.00139)	(0.00284)	(0.00389)	(0.00394)
EuropeanUnion*Post2019	-0.0996	-0.226**	0.0379	-0.0933	-0.227**	0.0353
	(0.0615)	(0.0905)	(0.0796)	(0.0645)	(0.0954)	(0.0822)
Constant	-0.309	-0.157	-0.464***	0.208	0.544	-0.270
	(0.219)	(0.302)	(0.161)	(0.552)	(0.780)	(0.629)
Observations	3,245	1,614	1,631	3,245	1,614	1,631
R-squared	0.140	0.190	0.239	0.542	0.524	0.568
Adjusted R-squared	0.128	0.168	0.219	0.482	0.459	0.509
Country Fixed Effects	Yes	Yes	Yes			
Industry Fixed Effects	Yes	Yes	Yes			
Institution Fixed Effects	No	No	No	Yes	Yes	Yes
Year Fixed Effects	Yes	Yes	Yes	Yes	Yes	Yes

Table A.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), and (4) use IntegratedStrategy, DiscussClimateRisk, LogCarbonOffsets, and PolicyEngagement as dependent variables, respectively. Regressions (1), (2), and (4) 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), and (4) use a probit model with EnvironmentalTeam, EnvironmentalProducts, SupplierClimateEngagement, and ClimateScenarioAnalysis as dependent variables, respectively. 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 are reported in parentheses. ***, **, and * indicate significance at the 1%, 5% and 10% levels, respectively.

Panel A: Transition risk

VARIABLES	(1) Integrated Strategy	(2) Discuss ClimateRisk	(3) Log CarbonOffsets	(4) Policy Engagement
$\hat{\beta}_{BMG}$ (t-1)	0.278**	0.371**	0.448*	-0.359*
	(0.121)	(0.155)	(0.264)	(0.199)
Beta (t-1)	0.243	0.408	0.869	0.941**
	(0.416)	(0.301)	(0.721)	(0.366)
LogMarketValue (t-1)	0.307*	0.531***	0.847**	0.442***
	(0.158)	(0.130)	(0.366)	(0.139)
Cash (t-1)	-3.393	3.434	1.944	5.991***
	(5.502)	(2.926)	(1.727)	(1.967)
NetIncome (t-1)	-9.251*	-4.110*	2.541	-0.612
	(5.548)	(2.484)	(2.328)	(2.290)
MtoB (t-1)	-0.106	-0.228**	-0.0363	-0.256**
	(0.152)	(0.114)	(0.170)	(0.115)
Debt (t-1)	-0.00119	0.0327***	-0.00627	-0.00684
	(0.00969)	(0.00804)	(0.0154)	(0.00624)
Environmental Transparency Score (t-1)	-0.773	2.451***		
	(0.887)	(0.872)		
Constant	-0.825	1.551	-4.920	-0.916
	(1.169)	(1.101)	(3.884)	(1.177)
Observations	581	657	335	812
R-squared			0.619	
Adjusted R-squared			0.337	
Country-Year FE	Yes	Yes	Yes	Yes
Industry-Year FE	Yes	Yes	Yes	Yes

Panel B: Physical risk

VARIABLES	(1) Environmental Team	(2) Environmental Products	(3) Climate Scenario Analysis	(4) Supplier Climate Engagement
$\hat{\beta}_{VMS}$ (t-1)	0.131***	0.104***	0.0963*	0.577***
	(0.0442)	(0.0363)	(0.0505)	(0.174)
Beta (t-1)	0.301	0.245	0.0312	0.162
	(0.245)	(0.235)	(0.321)	(0.544)
LogMarketValue (t-1)	0.552***	0.705***	0.541***	1.323***
	(0.0830)	(0.0853)	(0.100)	(0.287)
Cash (t-1)	1.387	5.540***	1.979	7.330*
	(1.309)	(1.419)	(1.736)	(4.252)
NetIncome (t-1)	-0.226	-2.444	-1.334	-6.297
	(1.591)	(1.749)	(2.905)	(3.924)
MtoB (t-1)	-0.152*	-0.194**	-0.0444	-0.160
	(0.0820)	(0.0893)	(0.0924)	(0.152)
Debt (t-1)	0.0121**	0.00612	0.00842	-0.0187*
	(0.00480)	(0.00486)	(0.00602)	(0.0109)
Constant	-4.089***	-5.777***	-4.391***	-4.565**
	(0.678)	(0.795)	(0.822)	(2.299)
Observations	1,256	1,341	757	353
R-squared				
Adjusted R-squared				
Country-Year FE	Yes	Yes	Yes	Yes
Industry-Year FE	Yes	Yes	Yes	Yes

Appendix B: Variable description

Table B.1

Risk factor description

Variable	Description
BMG	Transition risk factor, constructed as a long-short portfolio based on both estimated and reported GHG 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	Nontraded liquidity factor of Pástor and Stambaugh (2003) from https://faculty.chicagobooth.edu/lubos-pastor/data
ME	Difference between the returns on portfolios of small and large stocks from Hou-Xue-Zhang q-factors data library.
MKT	Difference between the returns on the market portfolio and the risk-free rate (Market factor) from Kenneth French website library.
ML	Interbank market liquidity indicator, calculated as the spread between the 3-month Euribor rate against the equivalent Overnight Indexed Swap rate.
NS	North–South spread, computed as the difference between the 10-year German sovereign bond rate against an average of Greece, Ireland, Italy, Spain, and Portugal's 10-year rates (from the European Central Bank Statistical Data Warehouse).
QMJ	Quality-minus-junk (QMJ) factor that invests long quality stocks and short junk stocks (Asness et al., 2019) from the AQR library.
RMW	Difference between the returns of robust and weak stocks (robust-minus-weak factor), based on operational profitability from Kenneth French website library.
ROE	Difference between the returns on portfolios of high and low profitability stocks (Return on Equity factor) from Hou-Xue-Zhang q-factors data library.
RR	Risk Reversal on the USD/EUR options from Bloomberg.
SMB	Difference between the returns on portfolios of small and large stocks (small-minus-big factor) from Kenneth French website library.
VMS	Physical risk factor, constructed as a long-short portfolio based on Trucost physical climate risk scores for all dead and active stocks reported in Refinitiv Eikon and listed on European equity markets (excluding financial sector companies). Alternatively, we use physical climate scores from ISS-ESG and 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).

Table B.2

Description of Financial and extrafinancial firm-level 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).
Debt	Ratio of total debt to total capital (from Datastream).
DiscussClimateRisk	Dummy variable equal to one if the Management Discussion and Analysis (MD&A) or its equivalent risk section of the financial institution's annual report discusses business risks related to climate change (CLIMATE_RISKS in Bloomberg).
Environmental Transparency Score	Score measuring the level of disclosure a financial institution offers for the fields under the Environmental Pillar, on a scale of 0 to 1 (ENVIRONMENTAL_PILLAR_DISCLOSURE in Bloomberg).
EnvironmentalProducts	Dummy variable equal to one if the financial institution has at least one product line or service that is designed to have positive effects on the environment (item ENPIDP019 in Datastream).
EnvironmentalTeam	Dummy variable equal to one if the financial institution has an environmental management team (item ENRRDP004 in Datastream).
Institutional ownership	Percentage of ownership by banks, insurance, and pension funds (sum of items S_122, S_128, and S_129 from the Securities Holdings Statistics database)
IntegratedStrategy	Dummy variable equal to one if the financial institution integrates extrafinancial factors in its management discussion and analysis (MD&A) section in the annual report (item CGVSDP018 in Datastream).
LogCarbonOffsets	Natural logarithm of the equivalent of the CO2 offsets, credits, and allowances purchased and/or produced by the financial institution during the year (item in Datastream, expressed in tons).
LogMarketValue	Natural logarithm of market capitalization (item MV in Datastream, expressed in million euros).
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).
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).
VerifiedScope3	Dummy variable equal to one if all of the financial institution's Scope 3 emissions have been verified by a third party (from CDP, item CDP_PCT_DATA_VERIFIED_SCOPE_3 in Bloomberg).

Table B.3

Description of country characteristics

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

Appendix C: VaR estimation

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

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

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

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 prespecified distribution and $\hat{\mu}_{i,t}$ is the mean returns of institution i at time t. For simplicity, $\hat{\mu}_{i,t}$ is estimated by 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. Since the sample size is moderate and we are not directly interested in the model's forecasting ability in this study, we only estimate the in-sample VaR.

Table C.1 evaluates the ability of our model to fit the data and to capture tail risk. We present the Akaike, Bayes, Shibata, and Hannan Quinn information criteria for various model specifications and error distribution assumptions (Panel A). We show that the GJR-GARCH model of Glosten et al. (1993) fits the data best compared 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.[26] 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 a heavier-tailed error distribution.

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

Table C.1

Model selection.

This table presents diagnostic tests for model selection and error distribution assumptions (see Equation A.3). Panel A reports the information criteria of Akaike, Bayes, Shibata, and Hannan Quinn. Panel B runs 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). It also indicates the expected number of VaR exceedances, the realized number of VaR exceedances and the standard deviation of the difference between the realized and expected number of VaR exceedances. GJR-GARCH, E-GARCH, NA-GARCH, and C-GARCH 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), respectively.

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

Panel B: VaR exceedance tests

Model	Error distribution	Expected VaR 5% exceed	Realized VaR 5% exceed	Standard deviation (Realized-Expected)	Number of rejections		
					VaR UC test	VaR CC test	VaR Duration test
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 D: Climate risk factors

D.1. Factor analysis

The cumulative returns of our climate risk factors are plotted in Figure D.1. We observe that the transition and physical risk factors have underperformed over time, which may 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 tends 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 D.1, 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 high-emitting firms tend to underperform low-emitting 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 nonfinancial companies.

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

Table D.2 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 sectoral concentration in both the long and short portfolio allocations. For example, firms from the personal goods and software industries, two low-emitting sectors, are most represented in the green portfolio, while companies from the oil and gas production industry, a very GHG-intensive sector, are most often found in the brown portfolio. Despite this concentration, the portfolios remain invested in all sectors, suggesting that our transition risk factor is well suited to capturing both the sectoral and company-level effects of transition climate risks. We also note that the divergence in firm size between the green and brown portfolios is relatively small compared to that of the difference in GHG 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 GHG 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 average physical risk scores of 62.4 and 32.0, respectively.[27] 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).

D.2. Factor robustness

[27] 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).

To alleviate the concern that our main conclusions in the rest of the article may depend on the specification of our climate risk factors, we evaluate the robustness of our key results 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[28]. The average correlation between the three factors is relatively low (27%), highlighting the existence of significant disagreement on the exposure of nonfinancial firms to physical risk. The difference in firm coverage across data providers may also mechanically reduce the correlation between the factors. However, our main results are robust to the various physical risk factor specifications (see Section 3.2). In all cases, we find no evidence that physical risks have significant effects on systemic risk within the financial sector. In addition to the fact that investors appear to view physical risk as a long-term risk (Stroebel and Wurgler, 2021), the lack of results may be explained by the disagreement between physical risk scores. Such a mismatch may create dispersion in investment flows in the event of a natural disaster, limiting or delaying the incorporation of physical risks into asset prices. This effect is examined by Billio et al. (2021) for ESG scores.

Finally, to alleviate the risk that our climate risk factors capture non-climate related characteristics, we conduct a placebo test. The idea of the test is to examine whether the climate

[28] 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.

risk factors significantly influence systemic risk within the financial sector over the period 1990–2005. Investors' awareness about climate change was limited at the time and climate data on GHG emissions and physical risk exposures were almost inexistent. As a result, we do not expect the returns of financial institutions to reflect climate risks over the selected period, but the noise of the factors could affect results. To perform this exercise, we download data for financial and nonfinancial equities from 1990 to 2005. Then, we reconstruct the climate risk factors based on the returns of nonfinancial firms from 1990 to 2005. To build the long and short portfolios, we use the average physical risk scores and GHG emission intensity for each firm from 2005 to 2022. The results are reported in Table OA.2 (Online Appendix). As expected, we find no significant impact of transition and physical climate risks on systemic risk within the European financial sector over the period.

Figure D.1

Cumulative returns of the climate risk factors

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

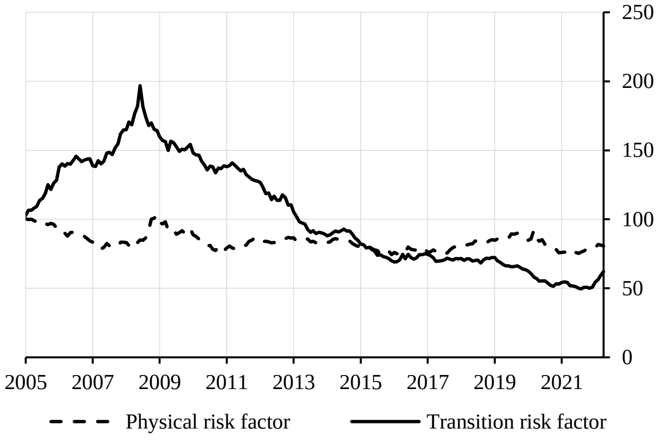


Table D.1

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 D.2

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 GHG 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 for high climate risk firms (>80th percentile) and short for low climate risk firms (<20th percentile).

Panel A: Transition risk factor

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

Panel B presents 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 for high climate risk firms (>80th percentile) and short for low climate risk firms (<20th percentile).

Panel B: Physical risk factor

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

Online Appendix

Table OA.1

Most interconnected institutions based on VaR and returns.

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

Pricing of climate risks within nonfinancial firms

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

Panel A: Portfolios based on GHG intensity

	Portfolios based on GHG intensity									
	q1	q2	q3	q4	q5	q6	q7	q8	q9	q10
BMG	-0.476***	-0.234***	-0.160*	-0.186**	-0.083	-0.118*	-0.026	0.167**	0.352***	0.474***
	(0.066)	(0.078)	(0.097)	(0.087)	(0.083)	(0.067)	(0.066)	(0.068)	(0.067)	(0.068)
MKT	0.669***	0.624***	0.571***	0.587***	0.558***	0.597***	0.647***	0.670***	0.673***	0.678***
	(0.053)	(0.064)	(0.064)	(0.062)	(0.062)	(0.059)	(0.053)	(0.056)	(0.054)	(0.050)
SMB	0.134	0.221	0.030	0.041	0.003	0.086	0.133	0.088	0.122	0.068
	(0.112)	(0.180)	(0.152)	(0.130)	(0.135)	(0.117)	(0.142)	(0.122)	(0.126)	(0.095)
HML	0.269*	0.314*	0.256	0.378**	0.370**	0.345**	0.147	0.367**	0.309***	0.415***
	(0.148)	(0.185)	(0.195)	(0.168)	(0.174)	(0.144)	(0.153)	(0.162)	(0.117)	(0.136)
RMW	0.444**	0.579*	0.510*	0.575**	0.712***	0.854***	0.506**	0.728***	0.455***	0.380**
	(0.226)	(0.303)	(0.291)	(0.235)	(0.260)	(0.216)	(0.239)	(0.212)	(0.160)	(0.180)
CMA	-0.355**	-0.399**	-0.361*	-0.273	-0.294	-0.152	-0.207	-0.373**	-0.472***	-0.515***
	(0.174)	(0.194)	(0.203)	(0.212)	(0.240)	(0.190)	(0.173)	(0.173)	(0.139)	(0.164)
WML	0.050	-0.039	0.036	0.029	0.016	0.006	-0.075	-0.030	0.021	0.009
	(0.055)	(0.081)	(0.067)	(0.062)	(0.059)	(0.083)	(0.066)	(0.058)	(0.065)	(0.051)
Constant	-0.002	-0.0005	0.001	0.0003	0.0004	-0.002	-0.0003	-0.001	-0.001	-0.001
	(0.002)	(0.003)	(0.003)	(0.002)	(0.002)	(0.002)	(0.002)	(0.002)	(0.002)	(0.002)
Observations	208	208	208	208	208	208	208	208	208	208
R-squared	0.765	0.659	0.626	0.666	0.624	0.649	0.688	0.727	0.769	0.819
Adjusted R^2	0.757	0.648	0.613	0.654	0.611	0.636	0.677	0.717	0.761	0.813

Panel B: Portfolios based on physical risk exposure

	Portfolios based on physical risk exposure									
	q1	q2	q3	q4	q5	q6	q7	q8	q9	q10
VMS	0.812***	0.143	0.067	0.150**	0.026	0.125	0.063	0.032	0.128**	-0.432**
	(0.119)	(0.115)	(0.077)	(0.075)	(0.069)	(0.092)	(0.081)	(0.112)	(0.062)	(0.203)
MKT	0.655***	0.645***	0.625***	0.705***	0.754***	0.638***	0.613***	0.597***	0.561***	0.620***
	(0.069)	(0.076)	(0.047)	(0.056)	(0.046)	(0.062)	(0.057)	(0.062)	(0.058)	(0.077)
SMB	0.260**	0.813***	-0.144*	0.227*	-0.034	-0.038	-0.292***	-0.187	-0.159	0.178
	(0.127)	(0.144)	(0.086)	(0.125)	(0.100)	(0.163)	(0.110)	(0.115)	(0.112)	(0.143)
HML	0.383**	0.532***	0.185	0.573***	0.477***	0.349	0.002	0.360**	-0.064	0.280
	(0.180)	(0.192)	(0.132)	(0.167)	(0.131)	(0.241)	(0.146)	(0.157)	(0.170)	(0.173)
RMW	0.637***	0.665**	0.410***	0.632***	0.630***	0.871**	0.363	0.886***	0.247	0.463**
	(0.234)	(0.295)	(0.150)	(0.234)	(0.200)	(0.354)	(0.223)	(0.202)	(0.191)	(0.219)
CMA	-0.471**	-0.585**	-0.255	-0.706***	-0.303**	0.009	0.060	-0.164	-0.205	-0.641***
	(0.200)	(0.298)	(0.182)	(0.214)	(0.133)	(0.278)	(0.182)	(0.194)	(0.218)	(0.197)
WML	-0.013	-0.005	0.126***	0.028	0.011	-0.048	-0.014	0.004	-0.021	0.029
	(0.051)	(0.066)	(0.042)	(0.053)	(0.055)	(0.076)	(0.065)	(0.048)	(0.070)	(0.055)
Constant	-0.003	-0.004	0.0003	-0.003	-0.003	-0.001	0.001	-0.001	0.002	0.0004
	(0.002)	(0.003)	(0.002)	(0.002)	(0.002)	(0.003)	(0.002)	(0.002)	(0.002)	(0.002)
Observations	208	208	208	208	208	208	208	208	208	208
R-squared	0.760	0.677	0.676	0.744	0.781	0.654	0.675	0.650	0.603	0.611
Adjusted R^2	0.751	0.665	0.665	0.735	0.773	0.642	0.663	0.638	0.589	0.597

Table OA.3

Placebo test (1990–2005)

This table presents the determinants of systemic risk based on the time series analysis described in Equation (10) over the period 1990–2005. 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 $\widehat{\Delta VaR}$ of the risk factors, as described in Section 2.5. For reasons of data availability, we adapt certain control variables. ML, DP and YC are constructed from US data. NS is based on the difference between the average rates of Ireland, Spain and Italy compared with Germany. RR is not available for the analysis period and has therefore been suppressed. Newey–West standard errors are reported in parentheses. ***, **, and * indicate significance at the 1%, 5% and 10% levels, respectively. Note that a positive coefficient always indicates that a degradation in the indicator is associated with an increase in systemic risk.

VARIABLES	(1) $\widehat{\Omega}_1$	(2) $\widehat{\Omega}_1$	(3) $\widehat{\Omega}_1$	(4) $\widehat{\Omega}_1$
BMG	-0.558	-0.640	-0.514	-0.887**
	(0.528)	(0.605)	(0.489)	(0.409)
VMS	4.998	1.824	3.721	0.006
	(3.414)	(1.801)	(4.024)	(1.329)
MKT	6.714***	6.249***		4.542***
	(1.340)	(1.345)		(0.814)
SMB	-2.149	-1.957		-2.642**
	(1.462)	(1.483)		(1.154)
HML	0.279	-0.140		-0.166
	(0.251)	(0.443)		(0.326)
RMW		1.371		1.479**
		(1.146)		(0.632)
CMA		-0.651		-0.186
		(0.718)		(0.642)
WML		0.800**		0.520**
		(0.359)		(0.240)
ML			2.380	2.976
			(3.019)	(2.075)
DP			96.623***	64.761***
			(21.403)	(13.927)
YC			86.522*	57.764***
			(52.466)	(22.037)
NS			5.818	6.556
			(6.358)	(5.156)
ES			0.140	0.091
			(0.186)	(0.160)
Constant	0.003	-0.013	-0.053	-0.048
	(0.279)	(0.295)	(0.221)	(0.205)
Observations	169	169	169	169
R-squared	0.522	0.557	0.480	0.714
Adjusted R-squared	0.508	0.535	0.457	0.690

Table OA.4

Bootstrapping approach – time series dimension

This table presents the determinants of systemic risk based on the time series analysis 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 $\widehat{\Delta VaR}$ of the risk factors, as described in Section 2.5. Standard errors are estimated based on a bootstrapping approach. Bias-corrected and accelerated 90% confidence intervals are shown in square brackets. Note that a positive coefficient always indicates that a degradation in the indicator is associated with an increase in systemic risk.

VARIABLES	(1) $\widehat{\Omega}_1$	(2) $\widehat{\Omega}_1$	(3) $\widehat{\Omega}_1$	(4) $\widehat{\Omega}_1$
BMG	**1.275** [0.462– 2.511]	**0.788** [0.012 – 1.902]	**1.135** [0.141 – 2.442]	**0.701** [0.055 – 1.636]
VMS	-0.033 [-2.777 – 3.683]	-1.205 [-4.128 – 2.229]	1.086 [-1.719 – 4.470]	-0.868 [-3.326 – 1.833]
MKT	**3.276** [2.585 – 3.919]	**3.183** [2.508 – 3.876]		**1.948** [1.164 – 2.521]
SMB	**11.441** [6.355 – 20.843]	**11.274** [6.886 – 21.254]		**5.497** [3.101 – 10.57]
HML	**6.061** [2.472 – 8.812]	**5.952** [0.579 – 9.041]		**2.096** [0.022 – 4.460]
RMW		-0.892 [-7.419 – 6.492]		3.369 [-0.640 – 7.813]
CMA		0.295 [-0.824 – 1.912]		0.129 [-0.786 – 1.205]
WML		**0.616** [0.266 – 1.220]		**0.469** [0.185 – 0.974]
ML			6.861 [-11.48 – 23.80]	-0.104 [-15.40 – 17.92]
DP			**7.089** [5.783 – 8.579]	**2.357** [0.957 – 4.312]
YC			-0.189 [-1.571 – 1.711]	0.463 [-0.834 – 2.004]
NS			**3.359** [0.896 – 7.464]	1.562 [-0.455 – 5.597]
RR			**-1.429** [-2.890 – -0.554]	-0.455 [-1.472 – 0.376]
ES			**1.657** [1.108 – 2.000]	**1.186** [0.852 – 1.693]
Constant	-0.054 [-0.668 – 0.449]	-0.060 [-0.729 – 0.439]	-0.058 [-0.703 – 0.369]	-0.052 [-0.552 – 0.369]
Observations	207	207	207	207
# resampling	9,999	9,999	9,999	9,999

Table OA.5

Bootstrapping approach – cross-sectional dimension

This table presents the cross-sectional analysis, as described in Equation (11). 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). Standard errors are estimated based on a bootstrapping approach. Bias-corrected and accelerated 90% confidence intervals are shown in square brackets.

VARIABLES	(1) $\hat{X}_1$	(2) $\hat{X}_1$	(3) $\hat{X}_1$	(4) $\hat{X}_1$
$\hat{\beta}_{BMG}$	**0.012** [0.006 – 0.018]	**0.012** [0.006 – 0.019]	**0.007** [0.002 – 0.012]	**0.007** [0.001 – 0.012]
$\hat{\beta}_{VMS}$	-0.001 [-0.003 – 0.001]	-0.0001 [-0.003 – 0.002]	0.001 [-0.000 – 0.003]	0.001 [-0.001 – 0.002]
$\hat{\beta}_{MKT}$	**0.013** [0.006 – 0.021]	**0.011** [0.002 – 0.018]		**0.026** [0.015 – 0.031]
$\hat{\beta}_{SMB}$	**0.004** [0.002 – 0.005]	**0.003** [0.002 – 0.005]		**0.003** [0.001 – 0.004]
$\hat{\beta}_{HML}$	**0.004** [0.001 – 0.007]	0.005 [0.000 – 0.008]		**0.007** [0.002 – 0.010]
$\hat{\beta}_{RMW}$		0.001 [-0.000 – 0.003]		0.001 [-0.001 – 0.002]
$\hat{\beta}_{CMA}$		0.004 [-0.002 – 0.011]		0.005 [-0.001 – 0.009]
$\hat{\beta}_{WML}$		**0.030** [0.011 – 0.047]		0.010 [-0.003 – 0.022]
$\hat{\beta}_{ML}$			**0.0002** [0.0000 – 0.0004]	**0.0005** [0.0001 – 0.0007]
$\hat{\beta}_{DP}$			**0.003** [0.002 – 0.004]	**0.007** [0.004 – 0.009]
$\hat{\beta}_{YC}$			0.0003 [-0.004 – 0.004]	-0.002 [-0.006 – 0.003]
$\hat{\beta}_{NS}$			**0.002** [0.001 – 0.004]	**-0.003** [-0.005 – -0.001]
$\hat{\beta}_{RR}$			0.003 [-0.001 – 0.007]	-0.006 [-0.011 – 0.0002]
$\hat{\beta}_{ES}$			**0.073** [0.059 – 0.086]	**0.053** [0.040 – 0.067]
Constant	**0.026** [0.021 – 0.030]	**0.023** [0.019 – 0.029]	**0.022** [0.018 – 0.026]	**0.013** [0.009 – 0.018]
Observations	371	371	371	371
# resampling	9,999	9,999	9,999	9,999

Table OA.6

Error-in-Variables – shrinkage

This table presents the cross-sectional analysis, as described in Equation (11). The dependent variable $\hat{X}_1$ represents the loadings of each financial institution on $\hat{\Omega}_1$. The explicative variables are the coefficients $\hat{\beta}^{shr}$ extracted from Equation (6) then adjusted following Equation (12). White heteroskedasticity-robust standard errors are reported in parentheses in columns (1) to (4). We include industry and country fixed effects and report clustered standard errors at the country level in columns (5) to (8).

VARIABLES	(1) $\hat{X}_1$	(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) $\hat{X}_1$
$\hat{\beta}_{BMG}$	0.023*** (0.008)	0.028*** (0.009)	0.002 (0.008)	0.010 (0.008)	0.026*** (0.010)	0.032* (0.017)	0.018** (0.008)	0.020* (0.011)
$\hat{\beta}_{VMS}$	0.003 (0.003)	0.005 (0.003)	-0.003 (0.002)	-0.003 (0.002)	0.004 (0.007)	0.004 (0.005)	-0.001 (0.003)	0.001 (0.002)
$\hat{\beta}_{MKT}$	0.070*** (0.009)	0.059*** (0.009)		0.066*** (0.008)	0.064** (0.026)	0.050* (0.028)		0.050*** (0.010)
$\hat{\beta}_{SMB}$	0.013*** (0.002)	0.012*** (0.002)		0.007*** (0.002)	0.015*** (0.002)	0.015*** (0.003)		0.013*** (0.004)
$\hat{\beta}_{HML}$	0.012*** (0.003)	0.014*** (0.004)		0.016*** (0.004)	0.012 (0.008)	0.018* (0.010)		0.016 (0.012)
$\hat{\beta}_{RMW}$		0.005** (0.002)		0.004** (0.002)		0.009 (0.005)		0.005 (0.003)
$\hat{\beta}_{CMA}$		0.027*** (0.007)		0.031*** (0.006)		0.030 (0.022)		0.029*** (0.011)
$\hat{\beta}_{WML}$		0.069*** (0.018)		-0.010 (0.015)		0.057* (0.033)		-0.007 (0.028)
$\hat{\beta}_{ML}$			-0.008 (0.007)	-0.030*** (0.007)			-0.015 (0.019)	-0.038*** (0.014)
$\hat{\beta}_{DP}$			0.001*** (0.0003)	0.001*** (0.0003)			0.0003 (0.0002)	0.001*** (0.0003)
$\hat{\beta}_{YC}$			0.008*** (0.002)	0.020*** (0.003)			0.018*** (0.003)	0.022*** (0.005)
$\hat{\beta}_{NS}$			0.025*** (0.006)	0.003 (0.006)			0.011*** (0.004)	-0.005 (0.010)
$\hat{\beta}_{RR}$			0.013*** (0.003)	-0.004 (0.003)			0.004 (0.003)	-0.008 (0.005)
$\hat{\beta}_{ES}$			0.179*** (0.017)	0.101*** (0.013)			0.195*** (0.046)	0.114*** (0.025)
Constant	0.008** (0.003)	0.004 (0.003)	0.007** (0.003)	-0.008** (0.003)				
Observations	371	371	371	371	371	371	371	371
R-squared	0.374	0.412	0.430	0.582	0.465	0.501	0.566	0.655
Adjusted R-squared	0.366	0.399	0.417	0.566	0.411	0.445	0.518	0.610
Country Fixed Effects	No	No	No	No	Yes	Yes	Yes	Yes
Industry Fixed Effects	No	No	No	No	Yes	Yes	Yes	Yes

Table OA.7

Error-in-Variables – IV method

This table presents the cross-sectional analysis, as described in Equation (11). The dependent variable $\hat{X}_1$ represents the loadings of each financial institution on $\hat{\Omega}_1$. The explicative variables are computed based on the IV method of Jegadeesh et al. (2023). White heteroskedasticity-robust standard errors are reported in parentheses in columns (1) to (4). We include industry and country fixed effects and report clustered standard errors at the country level in columns (5) to (8).

VARIABLES	(1) $\hat{X}_1$	(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) $\hat{X}_1$
$\hat{\beta}_{BMG}$	0.072*** (0.026)	0.093*** (0.033)	0.079*** (0.027)	0.069** (0.029)	0.085*** (0.016)	0.092*** (0.008)	0.077** (0.035)	0.084*** (0.017)
$\hat{\beta}_{VMS}$	-0.013 (0.008)	-0.015* (0.008)	0.017 (0.011)	0.008 (0.008)	-0.010 (0.012)	-0.013 (0.009)	0.017 (0.023)	0.018* (0.010)
$\hat{\beta}_{MKT}$	0.085*** (0.012)	0.084*** (0.015)		0.092*** (0.015)	0.064*** (0.014)	0.064*** (0.024)		0.075** (0.029)
$\hat{\beta}_{SMB}$	0.013*** (0.003)	0.009*** (0.003)		0.009** (0.004)	0.013*** (0.002)	0.010*** (0.002)		0.011*** (0.003)
$\hat{\beta}_{HML}$	0.781 (0.613)	1.727*** (0.613)		1.039 (0.663)	0.395 (0.930)	1.267* (0.691)		0.290 (0.982)
$\hat{\beta}_{RMW}$		0.009*** (0.002)		0.001 (0.003)		0.007*** (0.002)		-0.001 (0.003)
$\hat{\beta}_{CMA}$		-0.002 (0.007)		-0.006 (0.007)		-0.002 (0.009)		-0.006 (0.015)
$\hat{\beta}_{WML}$		0.234* (0.122)		0.252** (0.102)		0.111*** (0.022)		0.170 (0.208)
$\hat{\beta}_{ML}$			-0.002*** (0.001)	-0.001 (0.001)			-0.002*** (0.001)	-0.001** (0.0004)
$\hat{\beta}_{DP}$			0.015*** (0.003)	0.018*** (0.003)			0.018*** (0.004)	0.020*** (0.007)
$\hat{\beta}_{YC}$			0.007 (0.045)	0.086** (0.041)			0.008 (0.091)	0.088*** (0.026)
$\hat{\beta}_{NS}$			-0.010 (0.041)	-0.105** (0.051)			-0.040 (0.044)	-0.138*** (0.048)
$\hat{\beta}_{RR}$			0.002 (0.017)	0.018 (0.016)			0.013 (0.020)	0.027 (0.017)
$\hat{\beta}_{ES}$			0.156*** (0.047)	0.183*** (0.028)			0.119 (0.135)	0.157*** (0.035)
Constant	-0.161 (0.122)	-0.368*** (0.117)	0.001 (0.015)	-0.300** (0.124)				
Observations	371	371	371	371	371	371	371	371
R-squared	0.144	0.177	0.119	0.261	0.320	0.333	0.324	0.396
Adjusted R-squared	0.132	0.159	0.100	0.232	0.251	0.259	0.249	0.317
Country Fixed Effects	No	No	No	No	Yes	Yes	Yes	Yes
Industry Fixed Effects	No	No	No	No	Yes	Yes	Yes	Yes

Table OA.8

Alternative set of factors – time series dimension

This table presents the determinants of systemic risk based on the time series analysis 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 $\widehat{\Delta VaR}$ 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.

VARIABLES	(1) $\widehat{\Omega}_1$	(2) $\widehat{\Omega}_1$	(3) $\widehat{\Omega}_1$	(4) $\widehat{\Omega}_1$	(5) $\widehat{\Omega}_1$
BMG	1.532** (0.703)	2.003** (0.918)	2.239*** (0.814)	1.733** (0.752)	1.856** (0.724)
VMS	3.017 (2.152)	-0.844 (1.916)	0.138 (1.677)	2.936 (1.934)	1.242 (1.256)
MKT	3.764*** (0.459)	2.710*** (0.294)	2.709*** (0.304)		1.758*** (0.364)
SMB	21.651** (9.814)	4.068 (2.659)	2.742 (2.645)		1.721 (1.607)
IA	-4.291 (2.907)	-5.998*** (2.157)	-3.882** (1.884)		-0.764 (1.501)
ROE		-1.303 (0.936)	-0.798 (0.662)		-0.240 (0.581)
EG		10.854*** (1.936)	7.945*** (1.443)		3.924*** (1.339)
WML		0.002 (0.069)	-0.019 (0.068)		-0.049 (0.057)
LIQ			1.897*** (0.439)		1.134*** (0.276)
QMJ			-0.113 (0.076)		-0.164** (0.079)
ML				-8.087 (17.159)	-4.965 (12.483)
DP				7.988*** (1.048)	3.214*** (0.894)
YC				-0.264 (0.405)	0.150 (0.638)
NS				3.400*** (1.237)	0.762 (1.011)
RR				-1.234* (0.730)	-0.454 (0.568)
ES				1.564*** (0.131)	0.818*** (0.166)
Constant	-0.060 (0.428)	0.167 (0.316)	0.053 (0.268)	-0.260 (0.286)	-0.110 (0.187)
Observations	203	203	203	203	203
R-squared	0.737	0.870	0.899	0.880	0.928
Adjusted R-squared	0.730	0.865	0.893	0.875	0.922

Table OA.9

Alternative set of factor loadings – cross-sectional dimension

This table presents the cross-sectional analysis, as described in Equation (11). The dependent variable $\hat{X}_1$ represents the loadings of each financial institution on $\hat{\Omega}_1$. The explicative variables are the coefficients $\hat{\beta}$ extracted from Equation (6). White heteroskedasticity-robust standard errors are reported in parentheses in columns (1) to (4). We include industry and country fixed effects and report clustered standard errors at the country level in columns (5) to (8).

VARIABLES	(1) $\hat{X}_1$	(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) $\hat{X}_1$	(9) $\hat{X}_1$	(10) $\hat{X}_1$
$\hat{\beta}_{BMG}$	0.015***	0.012***	0.010***	0.015***	0.003*	0.012	0.010***	0.009***	0.011**	0.004
	(0.003)	(0.002)	(0.002)	(0.004)	(0.002)	(0.009)	(0.003)	(0.003)	(0.005)	(0.003)
$\hat{\beta}_{VMS}$	-0.001	0.003***	0.003***	-0.002**	0.002*	-0.001	0.002	0.002*	-0.002**	0.002
	(0.001)	(0.001)	(0.001)	(0.001)	(0.001)	(0.003)	(0.001)	(0.001)	(0.001)	(0.002)
$\hat{\beta}_{MKT}$	0.019***	0.020***	0.018***		0.029***	0.016	0.015***	0.013***		0.021***
	(0.004)	(0.004)	(0.004)		(0.004)	(0.017)	(0.003)	(0.004)		(0.004)
$\hat{\beta}_{SMB}$	0.004***	0.004***	0.004***		0.005***	0.003***	0.004***	0.004***		0.004***
	(0.001)	(0.001)	(0.001)		(0.001)	(0.001)	(0.001)	(0.001)		(0.001)
$\hat{\beta}_{IA}$	-0.001	0.001	0.001		0.001	-0.0004	0.001*	0.001		0.001
	(0.001)	(0.001)	(0.001)		(0.001)	(0.002)	(0.001)	(0.001)		(0.001)
$\hat{\beta}_{ROE}$		0.013***	0.014***		0.013***		0.015***	0.017***		0.015***
		(0.003)	(0.003)		(0.003)		(0.004)	(0.004)		(0.004)
$\hat{\beta}_{EG}$		0.008***	0.008***		0.008***		0.008***	0.008***		0.008***
		(0.001)	(0.001)		(0.001)		(0.001)	(0.001)		(0.002)
$\hat{\beta}_{WML}$		-0.015	-0.017		-0.050***		-0.0001	-0.004		-0.041*
		(0.017)	(0.018)		(0.017)		(0.014)	(0.023)		(0.025)
$\hat{\beta}_{LIQ}$			0.010		0.040**			0.017**		0.039**
			(0.015)		(0.016)			(0.009)		(0.016)
$\hat{\beta}_{QMJ}$			0.009**		0.014***			0.009**		0.013**
			(0.004)		(0.004)			(0.004)		(0.006)
$\hat{\beta}_{ML}$				-0.002	0.001				-0.003***	-0.002
				(0.003)	(0.002)				(0.001)	(0.005)
$\hat{\beta}_{DP}$				-0.0003**	0.0002*				-0.0003***	0.0001
				(0.0001)	(0.0001)				(0.0001)	(0.0001)
$\hat{\beta}_{YC}$				0.006***	0.007***				0.007***	0.008***
				(0.001)	(0.001)				(0.001)	(0.002)
$\hat{\beta}_{NS}$				-0.0004	-0.003**				-0.001*	-0.002
				(0.001)	(0.001)				(0.001)	(0.002)
$\hat{\beta}_{RR}$				-0.051	-0.087***				-0.025*	-0.064
				(0.034)	(0.023)				(0.015)	(0.042)
$\hat{\beta}_{ES}$				0.0003	-0.005**				0.001	-0.003
				(0.002)	(0.002)				(0.001)	(0.002)
Constant	0.022***	0.018***	0.017***	0.028***	0.011***					
	(0.003)	(0.003)	(0.003)	(0.003)	(0.003)					
Observations	371	371	371	371	371	371	371	371	371	371
R-squared	0.178	0.290	0.297	0.111	0.402	0.329	0.407	0.415	0.319	0.492
Adjusted R^2	0.167	0.274	0.278	0.092	0.375	0.261	0.341	0.346	0.243	0.422
Country FE	No	No	No	No	No	Yes	Yes	Yes	Yes	Yes
Industry FE	No	No	No	No	No	Yes	Yes	Yes	Yes	Yes