# The impact of climate transition risks on financial stability. A systemic risk approach

Javier Ojea-Ferreiro,[a*] Juan C. Reboredo,[b**] and Andrea Ugolini[c***]

a. Joint Research Centre of the European Commission (JRC)
b. Department of Economics. Universidade de Santiago de Compostela, Spain
c. Department of Economics, Management and Statistics. University of Milan-Bicocca, Italy

## Abstract

Transitioning to a low-carbon economy involves risks for the value of financial assets, with potential ramifications for financial stability. We quantify the systemic impact on financial firms arising from changes in the value of financial assets under three climate transition scenarios that reflect different levels of vulnerability to the transition to a low-carbon economy, namely, hot house world, orderly transition, and disorderly transition. We describe three systemic risk metrics computed from a copula-based model of dependence between financial firm returns and financial asset market returns: climate transition expected returns, climate transition value-at-risk, and climate transition expected shortfall. Empirical evidence for European financial firms over the period 2013-2020 indicates that the climate transition risk varies across sectors and countries, with banks and real estate firms experiencing the highest and lowest systemic impacts from a disorderly transition, respectively. We find that default premium, yield slope and inflation are the main drivers of climate transition risk, and that, in terms of capital shortfall, the cost of rescuing more risk-exposed financial firms from climate transition losses is relatively manageable. Simulation of climate risks over a five-year period shows that disorderly transition can be expected to imply significant costs for banks, while financial services and real estate firms remain more sheltered.

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[*] The views expressed in this article are those of the author and do not necessarily reflect those of the JRC. Responsibility for the information and views expressed therein lies entirely with the authors. Joint Research Centre of the European Commission. Via Enrico Fermi, 56, 21027 Ispra VA, Italy. E-mail: javier.ojea-ferreiro@ec.europa.eu. Tel +39 033278-9272.

[**] Universidade de Santiago de Compostela. Departamento de Fundamentos del Análisis Económico. Avda. Xoán XXIII, s/n, 15782 Santiago de Compostela, SPAIN. E-mail: juancarlos.reboredo@usc.es. Phone: +34 881811675. Fax: +34 981547134.

[***] University of Milan-Bicocca. Department of Economics, Management and Statistics. Piazza dell'Ateneo Nuovo, 1, 20126 Milano MI, ITALY. E-mail: andrea.ugolini@unimib.it.

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## Non-technical summary

In this research we address how climate transition risk, through its effects on asset prices, could impact financial stability. To that end, we characterize the behaviour of financial firm returns conditional on the dynamics of market returns for green, neutral, and brown assets, reflecting low, neutral, and high vulnerability, respectively, to transition to a low-carbon economy. We consider three climate transition scenarios coherent with the NFGS narrative: disorderly transition, hot house world and orderly transition, featured in terms of relative changes in green, neutral, and brown return. We then assess the systemic risk impact of those scenarios on financial firms in terms of the average return (climate transition expected return), the minimum returns with some confidence level (climate transition value-at-risk), and the average return below that minimum threshold (climate transition expected shortfall).

For European financial firms (banks, insurance companies, financial services companies, and real estate firms) over the period 2013-2020, we find that the systemic impact of climate transition scenarios differs widely across financial institutions. Banks experience a greater systemic impact in a disorderly transition than in a hot house world scenario, while the opposite occurs for the other financial subsectors, especially for real estate firms. We also find that the systemic impact of the different climate transition scenarios broadly diverges within financial firm groups (mainly within the bank group), yielding potential winners and losers, and we furthermore study to what extent the systemic impact on financial systems varies across Europe.

We assess the implications of climate-related systemic risk in terms of capital shortfalls. For banks, capital shortfalls are negligible in the orderly transition scenario; however, in the disorderly transition and hot house world scenarios, capital shortfalls are sizeable and concentrated in a small number of entities, although those capital shortfalls can be absorbed within the banking sector. For the remaining financial firms, we find that insurance firms experience small capital shortfalls in any climate transition risk scenario, whereas financial services and real estate firms experience modest capital losses in a hot house world scenario, but negligible capital losses in the remaining scenarios.

Finally, a forward-looking simulation of prospective climate transition measures for the upcoming five-year period suggests that banks may be at a significant disadvantage in a disorderly transition scenario; financial services and real estate firms are likely to experience significant systemic risk effects in the hot house world scenario; and the systemic risk impacts for insurance firms are moderate in size and similar across the disorderly and orderly climate transition scenarios.

# 1. Introduction

Transitioning towards a low-carbon economy entails risks that may impair the performance of firms, with potential ramifications for financial stability. Central banks have warned of the potential destabilizing effects of climate change risks[1] on financial stability (e.g., the Bank of England, 2017; De Nederlandsche Bank, 2017; ESRB, 2016),[2] and policymakers have underscored the potential of climate transition as a source of systemic risk.[3] Therefore, assessing the impact of climate transition risks on financial firms and on the stability of the financial system is currently high priority on the agenda of central banks, regulators, and investors (Carney, 2015; European Systemic Risk Board, 2016, Campiglio et al., 2018).

In this paper, we develop an empirical set-up to quantify the effects of climate transition risk on financial firms. We model the conditional distribution of financial firm returns, where the conditioning variables are market asset returns (categorized as green, neutral, and brown, reflecting low, neutral, and high vulnerability, respectively) in the transition towards a low-carbon economy. Based on financial firm return features and on the dependence of those returns on green, neutral, and brown asset returns, we obtain the conditional distribution of financial returns for three different climate transition scenarios: hot house world, disorderly transition, and orderly transition. Those scenarios are assumed to have different implications for the value of market assets: as described by their quantiles, in the hot house world scenario, brown and green assets experience upward and downward movements, respectively; in the disorderly transition scenario, green and brown assets experience upward and downward movements, respectively; and in an orderly transition scenario, green, neutral, and brown asset values remain in and around their median values.

We next assess the impact of each climate transition scenario on financial firm returns in terms of the average return of the conditional distribution, a left quantile of the conditional distribution, and the average return in the left tail of the conditional distribution, labelled climate transition expected return (CTER), climate transition value-at-risk (CTVaR), and climate transition expected shortfall (CTES), respectively. The three metrics are computed for individual

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[1] Climate change conveys two main type of risks: (a) physical risk, associated with the impact of extreme weather events such as droughts, floods, hurricanes, etc, and (b) transition risks that are related to the impact of changes in regulations, business models, technologies, and consumer preferences to be consistent with a low-carbon economy. This research focuses on the effects of transition risks on financial stability.

[2] The concerns of central banks regarding climate-related risk for financial system stability is also evidenced by the development of the Network for Greening the Financial System as an initiative of central banks and financial regulators (including the Bank of England and the De Nederlandsche Bank). It was created with the aim of fostering environment and climate risk management in the financial sector and mobilizing mainstream finance to support the transition toward a sustainable economy.

[3] See, e.g., https://www.ecb.europa.eu/press/blog/date/2021/html/ecb.blog210318~3bbc68ffc5.en.html.

financial firms from information on conditional copula functions that characterize dependencies between financial firms and market asset returns.

We apply our methodology to European financial firms, including banks, insurance companies, financial services companies, and real estate firms over the period 2013-2020. Our main findings are that the systemic impact of climate transition scenarios differs widely across financial institutions. Banks experience more systemic impacts in a disorderly transition than in a hot house world scenario, while the opposite occurs for the other firm types, but especially for real estate firms. We also find that the systemic impact of the different climate transition scenarios broadly diverges within financial firm groups (mainly within the bank group), yielding potential winners and losers, and we furthermore find that the extent of the systemic impact on financial systems varies in different European countries.

We additionally explore the effect of different financial firm and market features on climate transition systemic risk, concluding that price-to-book, leverage and return on assets determine systemic risk dynamics, while default risk and the yield slope shape systemic risk dynamics in the disorderly transition scenario. At the macroeconomic level, the unemployment rate influences systemic risk dynamics in all three scenarios for financial services and real state firms. Likewise, we assess the implications of climate-related systemic risk for financial firms in terms of capital shortfalls (Acharya et al., 2017, Brownless and Engle, 2017). For banks, we find that, while capital shortfalls are negligible in the orderly transition scenario, in the disorderly transition and hot house world scenarios, capital shortfalls are sizeable, but are concentrated in a small number of entities, and can be absorbed within the banking sector. For the remaining financial firms, we find that insurance firms experience small capital shortfalls in any climate transition risk scenario, whereas financial services and real estate firms experience modest capital losses in a hot house world scenario, but negligible capital losses in the remaining scenarios.

Finally, based on the structure of financial firm return dynamics and dependence between firm and market asset returns, we perform a forward-looking simulation for the upcoming five-year period to compute prospective climate transition measures. Empirical evidence suggests that banks may be at a significant disadvantage in a disorderly transition scenario, but are likely to be broadly unaffected in the other two climate transition scenarios. Financial services and real estate firms are likely to experience significant systemic risk effects in the hot house world scenario, while expected returns may be relatively better in the disorderly and orderly transition scenarios. For insurance firms, systemic risk impacts are moderate in size and similar across the disorderly and orderly climate transition scenarios.

Our study adds to the growing body of literature on the impact of climate-related risks on financial systems. Battiston et al. (2017), for their network-based climate stress-test of climate risk impact in green and brown scenarios, report that European bank exposure to the fossil-fuel sector is small (3%-12%), but is significant and heterogeneous to climate-policy sectors (40%-54%); they also report that the systemic impact of climate risk is expected to be moderate in an orderly transition scenario. Also for Europe, Weyzig et al. (2014) find that the fossil-fuel company revaluation risk for financial stability is limited. Dafermos et al. (2018), using a calibrated ecological macroeconomic model, indicate that climate change is likely to damage the liquidity of firms and negatively affect credit expansion and financial stability, suggesting that those negative climate-induced effects could be reduced by green quantitative easing. Stolbova et al. (2018) report how shocks from the introduction of climate policies generate feedback effects between the real economy and the financial sector that reinforce mispricing and risk transmission. In a recent study of bank exposure to a portfolio of stranded assets, Jung et al. (2021) report a climate stress-testing procedure to measure climate risk impact on the capital of large global banks, documenting substantial capital shortfalls for most of the studied banks.

We contribute to this strand of the literature by introducing a new empirical framework to assess the impact of climate transition risks under three climate transition scenarios, characterized in terms of relative changes in the value of assets with differing vulnerabilities to climate transition. Thus, each scenario accounts for the potential asset re-pricing effects of climate transition (Carney, 2015), with a systemic impact that depends on how a financial firm hedges climate risks, i.e., on its relative exposure to green, neutral, and brown assets. Our systemic risk measures, which can be readily computed using publicly available market data on individual financial firms and on market assets, can thus reflect changing market conditions – such as induced by the COVID-19 pandemic – and so facilitate timely identification of systemic climate-related risks from a financial stability perspective.

The remainder of the paper is laid out as follows. Section 2 develops our methodological approach, encompassing a description of climate transition scenarios, systemic risk metrics, and vulnerabilities of market assets to climate transition, and outlining the dependence structure as given by copula functions. Section 3 describes data for European financial firms. Section 4 discusses empirical results for the systemic risk impact of the different climate transition scenarios for the European financial system, for categories of financial firms, and for individual financial firms and countries. Section 5 analyses determinants of climate transition systemic risk. Section 6 evaluates the implications of each climate transition scenario in terms of financial firm capital shortfalls. Section 7 reports prospective evaluation of systemic risk, and Section 8 concludes.

## 2. Methods

To describe our modelling approach to assessing to what extent climate transition risks could impair financial firms and ultimately affect the stability of the financial system, we first outline climate transition scenarios and systemic risk metrics. We then characterize the exposure of market assets to transition risks and outline the dependence modelling approach to measuring the systemic impact of climate transition scenarios on financial institutions. Finally, we describe the estimation procedure for the dependence structure.

### *2.1 Climate transition scenarios and financial stability*

Consistent with the narratives for climate transition risk provided by the Network for Greening the Financial System (2020), we consider three scenarios: hot house world, disorderly transition to a green economy, and orderly transition to a green economy. In the hot house world scenario, current policies are preserved, emissions grow, and temperatures increase to by more than 3ºC. In this scenario, representing a low transition risk (with high physical risks), brown firms are expected to increase in value, and green firms to do the opposite. In the disorderly transition scenario, an active stance is adopted with climate policies aimed at mitigating emissions and reducing global warming below 2ºC, but those policies are introduced abruptly, resulting in higher transition risk. As a result, the value of green firms increases rapidly, while carbon-emitting firms experience severe drops in value. In the orderly transition scenario, climate policies are introduced that gradually become more severe, aimed at reducing emissions and limiting global warming to below 2ºC. In this context, the transition risk is moderate; since all firms will be able to gradually adapt to the new setup, their values are not expected to experience abrupt changes.

Each of the above-described scenarios can be characterized in terms of the joint movement of asset returns of companies that exhibit different levels of exposure to climate transition risk. Let $r_g, r_n$, and $r_b$ denote the market returns of green, neutral, and brown firms, respectively, with a joint distribution $F(r_g, r_n, r_b)$.

Thus, in a disorderly transition scenario, abrupt policy constraints on the use of carbon intensive energy may cause operational difficulties for firms that are more exposed to risk, ultimately affecting the value of their assets (e.g., assets may become stranded). In contrast, firms with lower exposure to transition risk face a privileged position in the market (unless highly exposed firms in the meantime adapt their production processes to the new circumstance). As a result, market expectations regarding green asset prices curve upwards, with the opposite happening for brown asset prices. This impact can be described in terms of upward and downward movements of green and brown asset market returns, as described by their quantiles: $r_g \geq q_g^{\beta}$ and $r_b \leq q_b^{\alpha}$, where the $\alpha$- and $\beta$-quantiles of green and brown asset returns are given by $P(r_b \leq q_b^{\alpha}) = \alpha$ and $P\left(r_g \leq q_g^{\beta}\right) = 1 - \beta$.

In a hot house world scenario (low transition risk), policy actions to favour transition are implemented slowly and tardily, and investors adjust their expectations accordingly. As brown firms have more time to offload stranded assets without suffering a large price impact, brown asset prices increase, while green asset prices decline as green firms lose the opportunity to boost their business. Thus, the relative price impact of a hot house world scenario can be described in terms of upward and downward movements of brown and green asset market returns, characterized by their quantiles as: $r_g \leq q_g^{\alpha}$ and $r_b \geq q_b^{\beta}$, where the $\alpha$- and $\beta$-quantiles of green and brown asset returns are given by $P(r_g \leq q_g^{\alpha}) = \alpha$ and $P\left(r_b \leq q_b^{\beta}\right) = 1 - \beta$. Arguably, the returns of neutral assets in both extreme scenarios receive no particular impact as they are barely affected by the transition to a low-carbon economy.

Finally, in the orderly transition scenario, policy constraints to meet climate transition goals are implemented smoothly, allowing firms to progressively adapt to the new business setting. Investors would expect, therefore, asset returns to move around their median values (i.e., with no abrupt price changes), described as: $q_b^L \leq r_b \leq q_b^U$, $q_n^L \leq r_n \leq q_n^U$ and $q_g^L \leq r_g \leq q_g^U$, where $q_j^L$ and $q_j^U$ are the lower and upper quantiles around the median for the asset $j = g, n, b$.

To identify potential vulnerabilities of financial firms in each of the three scenarios, we consider the systemic impact of each scenario on financial firm returns. Following the systemic risk literature (Acharya et al., 2017; Browless and Engle, 2015; Adrian and Brunnermeier, 2016),[4] systemic impact can be measured using the CTER, CTVaR, and CTES metrics, calculated from the conditional distribution of financial firm returns as follows.

Let $r_i$ be the market returns of financial firm $i$. The CTER is the expected return of financial firm $i$ in the event of a climate transition stress scenario. For a disorderly transition scenario, this return is defined as:

$$CTER_i = E\left(r_i \,\middle|\, r_g \geq q_g^{\beta}, r_b \leq q_b^{\alpha}; r_n\right)$$

[4] For a survey of this literature, see Benoit et al. (2017).

$$= \int_{-\infty}^{\infty} r_i \frac{f\left(r_i, r_g \geq q_g^\beta, r_b \leq q_b^\alpha; r_n\right)}{P\left( r_g \geq q_g^\beta, r_b \leq q_b^\alpha; r_n\right)} dr_i, \quad (1)$$

where the second equality follows from the definition of conditional expected value, and where $f(\cdot)$ denotes the joint density of financial institution *i* and the disorderly transition scenario; $P(\cdot)$ is the probability of the disorderly transition scenario determined by $F\left(r_g, r_n, r_b\right)$, and, finally, $f(\cdot)/P(\cdot)$ is the density of the financial institution *i* conditional on a disorderly transition scenario.[5] Changing the values of the conditional variables in Eq. (1), we easily obtain the value of CTER for a hot house world scenario as $E\left(r_i \,\middle|\, r_b \geq q_b^\beta, r_g \leq q_g^\alpha; r_n\right)$, whereas for an orderly transition scenario the value of CTER is given by: $E\left(r_i \mid q_b^L \leq r_b \leq q_b^U, q_g^L \leq r_g \leq q_g^U, q_n^L \leq r_n \leq q_n^U\right)$.

In addition, the systemic impact of a climate transition scenario can be also assessed using CTVaR, defined as the maximum possible loss of a financial institution in a climate transition scenario over a given time horizon for a confidence level of $1-\gamma$. For a disorderly transition scenario, this loss is given by:

$$CTVaR_i^\gamma = F^{-1}_{i|r_g \geq q_g^\beta, r_b \leq q_b^\alpha; r_n}(\gamma), \quad (2)$$

where $F_{i|r_g \geq q_g^\beta, r_b \leq q_b^\alpha; r_n}(\cdot)$ is the probability distribution of $r_i$ conditional on a disorderly transition scenario, with $CTVaR_i^\gamma$ as the quantile that verifies that $P\left(r_i \leq CTVaR_i^\gamma | r_g \geq q_g^\beta, r_b \leq q_b^\alpha; r_n\right) = \gamma$. Changing the conditional distribution in Eq. (2) by $F_{i|r_g \leq q_g^\alpha, r_b \geq q_b^\beta; r_n}(\cdot)$ or by $F_{i|q_b^L \leq r_b \leq q_b^U, q_g^L \leq r_g \leq q_g^U, q_n^L \leq r_n \leq q_n^U}(\cdot)$, we obtain the CTVaR for a hot house world and an orderly transition scenario, respectively.

Finally, the tail effects from a climate transition scenario can be assessed using the CTES, defined as the average value of the financial institution returns falling below its CTVaR value. For a disorderly transition scenario, this is defined as:

$$CTES_i^\gamma = E(r_i | r_g \geq q_g^\beta, r_b \leq q_b^\alpha, r_i \leq CTVaR_i^\gamma; r_n)$$

[5] Note that the semicolon in the density function $f(\cdot; r_n)$ and the probability of the climate scenario $P(\cdot; r_n)$ indicates that the density or the probability is defined taking into account possible interactions between the variables that could take place not directly but through the neutral asset ($r_n$).

$$= \int_{-\infty}^{CTVaR_i^\gamma} r_i \frac{f\left(r_i, r_g \geq q_g^\beta, r_b \leq q_b^\alpha; r_n\right)}{P\left(r_g \geq q_g^\beta, r_b \leq q_b^\alpha, r_i \leq CTVaR_i^\gamma; r_n\right)} dr_i. \quad (3)$$

As above, changing the values of the conditional variables in Eq. (3) obtains the CTES for the alternative hot house world and orderly scenarios.

To compute the values of the CTER, CTVaR, and CTES systemic risk measures under different climate transition scenarios, we need to characterize (a) the green, neutral, and brown nature of the assets in the market; and (b) the conditional probability distribution that accounts for the strength of dependence between the returns of a financial firm and the climate transition scenario, with a shape that determines the vulnerability of the financial firm to shocks from any given climate transition scenario. In the next two subsections we outline these two crucial ingredients of our modelling approach to quantifying the systemic effects of climate transition on financial stability.

### *2.2 Climate transition risk rating*

To assess the transition risk exposure to of individual firms, we use rated information on the vulnerability of the firm's value to transition to a low-carbon economy. This information is reported by Sustainalytics — a widely recognized leading provider of environmental, social, and governance (ESG) information.

On an annual basis, Sustainalytics computes a rating called the carbon risk score (CRS), which is based on firms' exposure to and management of carbon transition risk in 146 subindustries. Carbon exposure, which largely depends on the type of business, measures the extent to which carbon risk is materialized across the firm's value chain (including operations, products, and services). It is measured by subindustry and is specifically adjusted at the firm level by considering (a) company operations or product mix deviations with respect to its subindustry, and (b) the firm's financial strength and geographical components that could undermine the firm's capacity to address carbon risks. Management of carbon risk measures the firm's management ability and quality in terms of reducing emissions and related carbon risks. Management, which is characterized by implementation of company's policies, programmes and systems in operations, products, and services, is ultimately reflected in (a) reductions in carbon emissions, (b) reliance on fossil fuels, and (c) the development of greener products and services. Once carbon risk management is accounted for, the remaining risk is unmanaged carbon risk, defined as unmanageable risks that are beyond the control of the company and manageable risks that have not been accounted for.

For unmanaged carbon risk, Sustainalytics assigns a CRS score that evaluates the extent to which company's value is placed at risk by transition to a low-carbon economy. Accordingly, firms are rated with a CRS between 0 and 100, reflecting negligible (0), low (1 to 9.99), medium (10 to 29.99), high (30 to 49.99), and severe (50 or more) carbon transition risk.[6] As a transition risk measure, the CRS metric is more informative than carbon emissions according to Greenhouse Gas (GHG) Protocol Scopes 1, 2, and 3, as it considers not only carbon emission information, but also policy actions and policies to manage the impact of transition to a low-carbon economy on a firm's value. Moreover, information on CRS ratings is available to institutional and private investors, who can assess the resilience of their investments to climate transition risks (Reboredo and Otero, 2021).

Using firm-level CRS scores, we sort firms in quintiles in such a way that they are categorized as green or brown when included in the first and fifth quintiles, respectively, and as neutral otherwise. The distinctive feature of green, neutral, and brown firms is their vulnerability to transition to a low-carbon economy, with green (brown) firms exhibiting the lowest (highest) risk exposure, and neutral firms having average risk exposure. Using returns for all firms within each category, we compute green, neutral, and brown returns as the average returns for the companies included in the corresponding category.[7] Inter-dependence between green, neutral, and brown returns and dependence with the returns of financial firms determines the systemic impact of different climate transition scenarios.

### *2.3 Modelling dependence*

Measuring the systemic impact of climate transition scenarios on financial firms as per Eqs. (1)-(3) requires knowledge of the shape of the conditional density for each financial institution or, alternatively, of the joint density of financial firm $i$ and the climate transition scenario and the probability of that climate transition scenario.

We model probability distributions using copula functions, which allow flexible modelling of a multivariate distribution in terms of separate marginal and joint dependence features and report information on conditional dependence, joint tail dependence, and

[6] For a detailed analysis of the rating methods, see: https://www.morningstar.com/lp/low-carbon-economy.

[7] Alternatively, we could also use market weights to determine the returns of each asset category, even though the dynamics of the returns for each category could be mainly determined by a single firm with large market capitalization.

nonlinearities to accurately assess the systemic impact of tail events such as extreme climate transition scenarios.[8]

According to Sklar's (1959) theorem, the probability distribution of two market returns can be expressed in terms of a bivariate copula function as $F(r_j, r_h) = C_{jh}(F_j(r_j), F_h(r_h))$, where $C$ is a cumulative distribution copula with uniform marginal variables given by $F_j(r_j) = u_j$, $F_h(r_h) = u_h$, and where $F_j(r_j)$ and $F_h(r_h)$ denote the marginal distribution function of the $j$ and $h$ stock returns that stem from the corresponding densities, $f_j(r_j)$ and $f_h(r_h)$. Conditional marginal distribution functions can, moreover, be obtained from the conditional copula function as $F_{j|h}(r_j|r_h) = C_{j|h}(u_j|u_h) = \frac{\partial C_{jh}(u_j,u_h)}{\partial u_h}$. Similarly, for the trivariate case, the distribution function can be written in terms of a copula function as $F(r_j, r_h, r_k) = C_{jhk}(F_j(r_j), F_h(r_h), F_k(r_k))$, while the conditional marginal distribution for two variables or one variable is obtained as $F_{jh|k}(r_j, r_h|r_k) = C_{jh|k}(u_j|u_k, u_h|u_k)$ and $F_{j|hk}(r_j|r_h, r_k) = C_{j|hk}(u_j|u_h, u_k)$, with $u_j|u_k = C_{j|k}(u_j|u_k)$ and $u_j|(u_h, u_k) = C_{j|k,h}((u_j|u_h)|(u_k|u_h))$. The extension to larger return dimensions is straightforward.

Using the copula representation of the distribution and conditional distribution functions, we obtain the probability of the disorderly transition scenarios in terms of copulas as:[9]

$$P\left(r_g \geq q_g^{\beta}, r_b \leq q_b^{\alpha}; r_n\right) = \int_0^1 C\left(u_b \leq \alpha, u_g \geq 1-\beta | u_n\right) du_n, \tag{4}$$

where $C(u_b \leq \alpha, u_g \geq 1-\beta|u_n) = C_{b|n}(\alpha|u_n) - C_{bg|n}\left(C_{b|n}(\alpha|u_n), C_{g|n}(1-\beta|u_n)\right)$. Swapping around the green and brown subscripts we obtain the probability for the hot house world scenario. The probability for an orderly transition scenario is given by:

$$P\left(q_b^U \geq r_b \geq q_b^L, q_g^U \geq r_g \geq q_g^L, q_n^U \geq r_n \geq q_n^L\right)$$
$$= \int_{0.5-\frac{\delta}{2}}^{0.5+\frac{\delta}{2}} C\left(0.5 - \frac{\alpha}{2} \leq u_b \leq 0.5 + \frac{\alpha}{2}, 0.5 - \frac{\beta}{2} \leq u_g \leq 0.5 + \frac{\beta}{2} | u_n\right) du_n, \tag{5}$$

where

[8] For a detailed analysis of copulas, see Joe (1997) and Nelsen (2006).

[9] Proofs for all equations that appear in this section are reported in Appendix A.

$C\left(0.5-\frac{\alpha}{2} \le u_b \le 0.5+\frac{\alpha}{2}, 0.5-\frac{\beta}{2} \le u_g \le 0.5+\frac{\beta}{2} | u_n\right) = C_{bg|n}\left(C_{b|n}(a|u_n), C_{g|n}(b|u_n)\right) +$
$C_{bg|n}\left(C_{b|n}(d|u_n), C_{g|n}(e|u_n)\right) - C_{bg|n}\left(C_{b|n}(a|u_n), C_{g|n}(e|u_n)\right) -$
$C_{bg|n}\left(C_{b|n}(d|u_n), C_{g|n}(b|u_n)\right)$,

with $P\left(q_j^U \ge r_j \ge q_j^L\right) = \eta$, $P\left(r_j \le q_j^U\right) = 0.5+\frac{\eta}{2}$ and $P\left(r_j \le q_j^L\right) = 0.5-\frac{\eta}{2}$ with $\eta = \alpha, \beta, \delta$ for $j = g, n, b$; and where $a = 0.5+\frac{\alpha}{2}$, $b = 0.5+\frac{\beta}{2}$, $d = 0.5-\frac{\alpha}{2}$ and $e = 0.5-\frac{\beta}{2}$.

Interestingly, the conditional copulas required to compute the probability of different climate transition scenarios as per Eqs. (4) and (5) derive from a specific hierarchical dependence structure among green, neutral, and brown assets in the market, as shown in the upper panel in Figure 1. This dependence is given by a C-vine copula,[10] where the central node in the first tree ($T_1$) represents neutral asset returns. Edges connecting two nodes capture joint dependence between the returns of those nodes through bivariate copulas, allowing conditional dependence between those two variables to be computer. Likewise, the second tree ($T_2$) reflects two nodes representing green and brown asset returns conditional on neutral asset returns, with the edge providing information on the joint dependence between those variables as given by the corresponding copula. For the three bivariate copulas arising from this dependence structure, we can obtain all conditional copulas involved in Eqs. (4) and (5), and so can compute the probability of the different climate transition scenarios.

[INSERT FIGURE 1 HERE]

Describing the joint density between the returns of a financial institution *i* and the climate transition scenario in terms of copulas, for a disorderly transition scenario this is derived as:

$$f\left(r_i, r_g \ge q_g^{\beta}, r_b \le q_b^{\alpha}; r_n\right) = \int_0^1 C\left(u_b \le \alpha, u_g \ge 1-\beta \middle| u_n, u_i\right) f_i\left(F_i^{-1}(u_i)\right) du_n, \tag{6}$$

where

$C\left(u_b \le \alpha, u_g \ge 1-\beta \middle| u_n, u_i\right) = C_{b|i,n}\left(C_{b|n}(\alpha|u_n)|u_i\right) -$
$C_{bg|i,n}\left(C_{b|i,n}\left(C_{b|n}(\alpha|u_n)\middle|u_i\right), C_{g|i,n}\left(C_{g|n}(1-\beta|u_n)\middle|u_i\right)\right)$, and where $f_i(r_i)$ is the density of returns for a financial firm *i* with joint distribution $F_i(r_i)$, such that $u_i = F_i(r_i)$. Swapping

[10] In the trivariate case, the C- and D-vine copulas are equivalent when the pivotal node in the first tree of the C-vine is the central node in the first tree of the D-vine. For an analysis of vine copulas, see Bedford and Cooke (2002); Kurowicka and Cooke, 2006; Aas et al., 2009.

around the green and brown subscripts, the density for the hot house world scenario follows. As for the orderly transition scenarios, density is computed as:

$$
\begin{aligned}
f\left(r_i, q_b^U \geq r_b \geq q_b^L, q_g^U \geq r_g \geq \ q_g^L, q_n^U \geq r_n \geq q_n^L\right) \\
= \int_{0.5-\frac{\delta}{2}}^{0.5+\frac{\delta}{2}} C\left(d \leq u_b \leq a, e \leq u_g \leq b \middle| u_n, u_i\right) f_i(F_i^{-1}(u_i))\ du_n,
\end{aligned}
\tag{7}
$$

where

$$
\begin{aligned}
C\left(d \leq u_b \leq a, e \leq u_g \leq b \middle| u_n, u_i\right) = \ & C_{bg|n,i}\left(C_{b|n,i}(a|\{u_n, u_i\}), C_{g|n,i}(b|\{u_n, u_i\})\right) + \\
& C_{bg|n,i}\left(C_{b|n,i}(d|\{u_n, u_i\}), C_{g|n,i}(e|\{u_n, u_i\})\right) - C_{bg|n,i}\left(C_{b|n,i}(a|\{u_n, u_i\}), C_{g|n,i}(e|\{u_n, u_i\})\right) - \\
& C_{bg|n,i}\left(C_{b|n,i}(d|\{u_n, u_i\}), C_{g|n,i}(b|\{u_n, u_i\})\right).
\end{aligned}
$$

Interestingly, the conditional copulas that are necessary to obtain the joint densities as per Eqs. (6) and (7) can be obtained from a specific hierarchical dependence structure between the financial institution and the assets in the market, represented in the lower (shaded) panel in Figure 1 through a C-vine copula. The first tree ($\bar{T}_1$) connects the returns of the financial firm with the two nodes of the second tree ($T_2$) of the hierarchical dependence of the assets in the market. From the three bivariate copulas that characterize this dependence structure, we can obtain the conditional copulas in Eqs. (6) and (7) that involve financial institution *i*.

Using the probabilities of climate transition scenarios as given by Eqs. (4)-(5), and the joint densities of financial institution *i* and climate transition scenarios as per Eqs (6)-(7), we can compute $CTER_i$ from copulas. Thus, for a disorderly transition scenario, the $CTER_i$ is computed as:

$$
\begin{aligned}
& E\left(r_i \middle| r_g \geq q_g^{\beta}, r_b \leq q_b^{\alpha}; r_n\right) \\
& = \frac{1}{P\left(r_g \geq q_g^{\beta}, r_b \leq q_b^{\alpha}; r_n\right)} \int_0^1 \int_0^1 F_i^{-1}(u_i)\, C\left(u_b \leq \alpha, u_g \geq 1-\beta \middle| u_n, u_i\right) du_n du_i,
\end{aligned}
\tag{8}
$$

where

$C\left(u_b \leq \alpha, u_g \geq 1-\beta \middle| u_n, u_i\right) = C_{b|i,n}\left(C_{b|n}(\alpha|u_n)\middle|u_i\right) -$
$C_{bg|i,n}\left(C_{b|i,n}\left(C_{b|n}(\alpha|u_n)\middle|u_i\right), C_{g|i,n}\left(C_{g|n}(1-\beta|u_n)\middle|u_i\right)\right)$, and $P\left(r_g \geq q_g^{\beta}, r_b \leq q_b^{\alpha}; r_n\right)$ is given by Eq. (4). For the hot house world scenario, the value of the $CTER_i$ is obtained by

swapping around the green and brown subscripts. For an orderly transition scenario $CTER_i$ is computed as:

$$E\left(r_i \middle| q_b^U \geq r_b \geq q_b^L, q_g^U \geq r_g \geq q_g^L, q_n^U \geq r_n \geq q_n^L\right) = \frac{1}{P\left(q_b^U \geq r_b \geq q_b^L, q_g^U \geq r_g \geq q_g^L, q_n^U \geq r_n \geq q_n^L\right)} \int_0^1 F_i^{-1}(u_i) \int_{0.5-\frac{\delta}{2}}^{0.5+\frac{\delta}{2}} C\left(d \leq u_b \leq a, e \leq u_g \leq b \middle| u_n, u_i\right) du_n du_i, \tag{9}$$

where $P\left(q_b^U \geq r_b \geq q_b^L, q_g^U \geq r_g \geq q_g^L, q_n^U \geq r_n \geq q_n^L\right)$ is given by Eq. (5).

$CTVaR_i^\gamma$ in Eq. (2) can also be computed using the copula representation of probabilities. For a disorderly transition scenario, the $CTVaR_i^\gamma$ is the quantile that verifies that $P\left(r_i \leq CTVaR_i^\gamma \middle| r_g \geq q_g^\beta, r_b \leq q_b^\alpha; r_n\right) = \gamma$, namely:

$$\frac{P\left(r_i \leq CTVaR_i^\gamma, r_g \geq q_g^\beta, r_b \leq q_b^\alpha; r_n\right)}{P\left(r_g \geq q_g^\beta, r_b \leq q_b^\alpha; r_n\right)} = \gamma$$

where $P\left(r_g \geq q_g^\beta, r_b \leq q_b^\alpha; r_n\right)$ is given by Eq. (4), and

$$P\left(r_i \leq CTVaR_i^\gamma, r_b \leq q_b, r_g \geq q_g; r_n\right) = \int_0^{F_i\left(CTVaR_i^\gamma\right)} \int_0^1 C\left(u_b \leq \alpha, u_g \geq 1-\beta \middle| u_n, u_i\right) du_n du_i. \tag{10}$$

where $F_i\left(CTVaR_i^\gamma\right) = P(r_i \leq CTVaR_i^\gamma)$. The $CTVaR_i^\gamma$ can thus be computed from copulas as:

$$CTVaR_i^\gamma = F_i^{-1}(G^{-1}(\gamma)), \tag{11}$$

where $G(\cdot)$ is a function given by the ratio between Eqs. (10) and (4). For the hot house world scenario, the $CTVaR_i^\gamma$ is obtained by swapping around the green and brown subscripts. For an orderly transition scenario, the function $G(\cdot)$ is given by the ratio between:

$$P\left(r_i \leq CTVaR_i^\gamma, q_b^U \geq r_b \geq q_b^L, q_g^U \geq r_g \geq q_g^L, q_n^U \geq r_n \geq q_n^L\right) = \int_0^{F_i\left(CTVaR_i^\gamma\right)} \int_{0.5-\frac{\delta}{2}}^{0.5+\frac{\delta}{2}} C\left(d \leq u_b \leq a, e \leq u_g \leq b \middle| u_n, u_i\right) du_n du_i \tag{12}$$

and Eq. (5).

Finally, for a disorderly transition scenario, $CTES_i^\gamma$ can be written in terms of copulas as:

$$E\left(r_i \,\middle|\, r_g \geq q_g^\beta, r_b \leq q_b^\alpha, r_i \leq CTVaR_i^\gamma; r_n\right) = \frac{1}{P\left(r_g \geq q_g^\beta, r_b \leq q_b^\alpha, r_i \leq CTVaR_i^\gamma; r_n\right)}$$

$$\int_0^{F_i\left(CTVaR_i^\gamma\right)} \int_0^1 F_i^{-1}(u_i)\, C(u_b \leq \alpha, u_g \geq 1-\beta | u_n, u_i) du_n du_i, \tag{13}$$

where

$$P\left(r_g \geq q_g^\beta, r_b \leq q_b^\alpha, r_i \leq CTVaR_i^\gamma; r_n; r_n\right)$$
$$= \int_0^{F_i\left(CTVaR_i^\gamma\right)} \int_0^1 C\left(u_b \leq \alpha, u_g \geq 1-\beta \middle| u_n, u_i\right) du_n du_i. \tag{14}$$

Swapping around the green and brown subscripts we obtain $CTES_i^\gamma$ for the hot house world transition scenario, while for an orderly transition scenario the joint density is given by:

$$f\left(r_i \leq CTVaR_i^\gamma, q_b^U \geq r_b \geq q_b^L, q_g^U \geq r_g \geq q_g^L, q_n^U \geq r_n \geq q_n^L\right)$$
$$= \int_0^{F_i\left(CTVaR_i^\gamma\right)} f\left(r_i, q_b^U \geq r_b \geq q_b^L, q_g^U \geq r_g \geq q_g^L, q_n^U \geq r_n \geq q_n^L\right) du_i, \tag{15}$$

and the probability of that scenario is given by Eq. (12).

### *2.4 Dependence structure estimation*

The dependence structure represented in Figure 1 is estimated using the two-step inference functions for margins (IFM) approach (Joe and Xu, 1996).

In the first IFM step, we estimate the univariate marginal distribution functions of the $j = i, g, n, b$ returns by maximum likelihood (ML), where the dynamics of those returns is assumed to be described by an autoregressive moving average (ARMA) model of order *m* and *k*:

$$r_{j,t} = \phi_0 + \sum_{q=1}^{m} \phi_q r_{j,t-q} + \sum_{k=1}^{k} \varphi_k \epsilon_{j,t-k} + \epsilon_{j,t}\,, \tag{16}$$

where $\phi_q$ and $\varphi_r$ denote the parameters of the AR and MA components of the model, and $\epsilon_{j,t}$ is the stochastic component that is assumed to have a zero mean and a variance with a dynamic behaviour represented by a threshold generalized autoregressive conditional heteroskedasticity (TGARCH) model:

$$\sigma_{j,t}^2 = \omega_0 + \sum_{k=1}^{K} \beta_q \sigma_{j,t-k}^2 + \sum_{h=1}^{H} \alpha_h \epsilon_{j,t-h}^2 + \sum_{h=1}^{H} \delta_h 1_{t-h} \epsilon_{j,t-h}^2, \tag{17}$$

where $\omega_0$, $\beta_q$ and $\alpha_h$ are the parameters of the volatility model, and where $1_{t-h} = 1$ if $\epsilon_{j,t-h} < 0$, and otherwise is zero. The parameter $\delta_h$ accounts for the asymmetric effect of shocks, thus, for $\delta_h > 0$, negative shocks have more impact on variance than positive shocks. Asymmetries and fat tails in the marginal distribution of returns are captured by assuming that the return distribution is given by Hansen's (1994) skewed-t density with $\vartheta$ $(2 < \vartheta < \infty)$ degrees of freedom and asymmetry parameter $\lambda$ $(-1 < \lambda < 1)$. From marginal models, we obtain the pseudo-sample observations for the copula as given by the integral probability transformation of standardized returns. The number of lags for the mean and variance of returns is selected using the Akaike information criterion (AIC).

In the second IFM step, we estimate the copula parameters by ML as follows. First, we estimate the parameters of the dependence model for the green, neutral, and brown assets as represented in the upper panel in Figure 1 (common for all financial institutions). This estimation uses sequential ML (Aas et al. 2009; Hobaek Haff, 2013), which consists of estimating bivariate copula parameters for the first tree level using the probability integral transformations from marginals as pseudo-sample observations, and then obtaining pseudo-sample observations from those copulas to estimate copula parameters for the next tree. Second, for each financial institution *i* we estimate the dependence structure of that financial institution with the market assets as represented in the lower panel in Figure 1. Bivariate copula parameters are estimated using sequential ML: copulas for the first tree are estimated using both pseudo-observations from the second tree of the dependence model (the conditional copula values for green and brown assets) and pseudo-sample observations from the probability integral transformation of the marginal of financial firm *i* returns, and then, from the bivariate copulas in the first tree we generate pseudo-observation to estimate the parameters of the copula in the second tree.

For the estimation of all the bivariate dependencies represented in Figure 1, we use different bivariate copula specifications as reported in Table 1, selecting the most appropriate copula model using the AIC corrected for small sample bias (Breymann et al., 2003).

[INSERT TABLE 1 HERE]

## 3. Data

Our sample includes large European financial firms and European listed firms that are annually rated with a CRS. The sample goes from 2013, when information on CRS at the firm level becomes available, to 2020. All data was sourced from Bloomberg. The sample includes 939 European listed firms, representing 99.4% of the firms included in the Eurostoxx-600 index and 97% of market capitalization of that index at the end of 2020. Those firms are annually grouped into the green, neutral, or brown asset categories, depending on whether they belong to the first CRS quintile, the second, third, and fourth CRS quintiles, or the fifth CRS quintile, respectively. As indicated above, weekly returns for each asset class are computed as the average of the log price returns of the assets in that category.

The sample of European financial firms includes 190 firms representing 85% of the Euro Stoxx financials index (data for the end of 2020): 43 banks (24 of which are classified as domestic systemically important banks by the Financial Stability Board in 2020), 36 insurance companies, 52 financial services companies, and 59 real estate firms. We consider various categories of financial firms given that their different business models are likely to affect their exposure to climate transition risks. Systemic risk for similar financial firms has been investigated by Engle et al. (2015) and for a similar set of banks by Borri and Giorgio (2021). By market capitalization (data for the end of 2020), the largest firms are as follows: HSBC, BNP Paribas, Banco Santander, and Intesa Sanpaolo (banks); Allianz, Chubb, Zurich Insurance, and AXA (insurance companies); UBS Group, London Stock Exchange, Deutsche Böerse, and Credit Suisse (financial services firms); and Deutsche Wohnen, Segro, Gecina, and LEG Immobilien (real estate firm). Total capitalization is 1,680 billion euros, for a median value of 10 billion euros. For all the financial firms, we compile data for weekly market prices in euros, and obtain (from Compustat) data on debt book value, the market value of the equity in euros and balance sheet information.

Table 2 presents summary statistics for the returns of different asset and financial firm categories. It confirms that green, neutral, and brown assets have dissimilar performances in terms of returns and volatilities, with green assets outperforming brown and neutral assets in terms of greater realized returns and lower volatility. Moreover, probability distributions of green, neutral, and brown assets also differ according to skewness and kurtosis information, and according to tail behaviour as reflected in the empirical value-at-risk (VaR) and expected shortfall (ES) values in the left and right sides of the distribution. Extreme movements in the green, neutral, and brown returns are dissimilar, with brown assets experiencing larger extreme downward movements than green assets. For the financial sample, Table 2 shows that financial services companies outperform the other categories, while real estate and insurance companies have similar average returns. Banks yield average negative returns and display greater volatility than the other financial firms. All financial firms are characterized by higher volatility than market assets, and by negative skewness and fat tails. According to the empirical VaR and ES metrics, banks show higher levels of tail risk than the other financial firms.

[INSERT TABLE 2 HERE]

Figure 2 shows the cumulative performance of green, neutral, and brown assets, along with the (average) cumulative returns for each financial institution category. Over the sample period, cumulative returns for the green assets are above the cumulative returns for brown assets, although the differences were slightly reduced in the last year of the sample period due to the COVID-19 pandemic. Financial firms show different patterns, with banks underperforming the other financial firms and experiencing severe cuts between mid-2015/mid-2016 and from the pandemic outset. Financial services and real estate returns display similar dynamics, closely co-moving with neutral asset returns.

[INSERT FIGURE 2 HERE]

To assess average exposure of financial firms to green, neutral, and brown assets, for each financial firm we run a capital asset pricing model (CAPM)-type regression, where the market return factor is decomposed into green, neutral, and brown asset returns, and with the three regression betas providing information on the sensitivity of each financial firm's returns to the different asset returns. The product of those betas multiplied by the respective average value of green, neutral, and brown asset returns under specific climate transition scenarios yields the average impact of a particular scenario on a financial institution. We assess those average impacts in three circumstances, as follows: (a) green and brown returns are above and below their respective median values, reflecting a disorderly transition scenario using median quantiles as thresholds; (b) brown and green returns are above and below their respective median values, reflecting a hot house world scenario using medians as thresholds; and (c) the returns of green, neutral, and brown assets are below their 75% and above their 25% respective quantiles, consistent with an orderly transition scenario.

Panel A in Figure 3 shows the distribution of betas across the financial firms included in different categories. The graphic evidence indicates that banks and insurance companies are more exposed to brown than to green asset returns, whereas financial services and real estate firms are more sensitive to green and neutral asset returns than to brown assets. Banks overall show the highest average beta for brown returns. There is also wide dispersion in the betas within each financial firm category, with the betas for neutral assets exhibiting the highest dispersion, with the exception of real estate firms.

Consistent with the distribution of betas, the distribution of average impacts from different climate transition scenarios differs widely across and within different categories of financial firms, as reflected in Panel B in Figure 3. Specifically, banks receive the highest positive and lowest positive average return impact from a hot house world scenario and a disorderly transition scenario, respectively, whereas the opposite occurs for real estate firms. The average impact for insurance firms is similar for different transition scenarios, while for financial services, the impact of a disorderly transition scenario is slightly more positive than of a hot house world scenario. Finally, graphically reflected is a wide diversity in the size of the impact within and between climate transition scenarios.

[INSERT FIGURE 3 HERE]

# 4. Empirical evidence on the systemic impact of climate transition

## *4.1 Model estimation*

We start by estimating marginal model parameters for green, neutral, and brown returns and for each financial firm in our sample. Table 3 reports estimates, where the number of lags in the mean and variance specifications are the values that minimize the AIC, considering different values between 0 and 2. Evidence for green, neutral, and brown marginal densities reported in the first three columns of Table 3 shows that those returns exhibited no serial dependence, whereas conditional variances were persistent and displayed significant positive leverage effects, with bad news having a greater impact on volatility than good news. The distribution of green, neutral, and brown assets is negatively skewed and has fat tails. Goodness-of-fit metrics for the model residuals point to the fact that no serial correlation remains, in either the residuals in levels or the residuals squared, and that the skewed-t distribution adequately accounts for the asymmetry and tail return features, given that the Kolmogorov-Smirnov test supports uniformity in the standardized model residuals.

[INSERT TABLE 3 HERE]

As the number of marginal models for the financial firms is large, rather than individual parameter estimates and goodness-of-fit results, we report only summary statistics for firms grouped into the four categories reported in the last four columns of Table 3. Overall, some financial firms show evidence of serial correlation in returns, volatility is persistent (mainly for banks), and there is some evidence of positive leverage effects for financial firms that is smaller in size than for market assets. Goodness-of-fit tests support the fitted marginal models, reporting no misspecification errors for any of the financial firms and confirming that the return distribution is well characterized by a skewed student-t with fat tails, which, in some cases, behaves as a symmetric student-t.

From marginal model estimations, we first estimate the market dependence structure (see the upper panel in Figure 1). Parameter estimates for the three estimated copulas that describe the dependence structure for green, neutral, and brown assets are shown in Table 4. The copula that best characterizes dependence between green and neutral assets is a static BB1 copula with average positive dependence and asymmetric tail dependence (greater lower tail dependence). Dependence between brown and neutral assets is also well described by a BB1 copula, with positive dependence oscillating over time, basically influenced by one of the copula parameters. Finally, conditional dependence between green and brown assets is well characterized by an independent copula, i.e., the product of the conditional distribution on the neutral asset.

[INSERT TABLE 4 HERE]

Table 5 summarizes estimations of the dependence structure between financial firms and the market (see the lower (shaded) panel in Figure 1). Copula estimates indicate that dependence between financial institutions and green returns is positive for most of the financial firms, with some evidence of independence for 22.2% of firms. Likewise, dependence between financial firms and brown returns conditional on neutral asset returns is mostly positive and low, with evidence of independence for 31.1% of firms. Consistent with the market dependence information, green and brown returns conditional on neutral and financial institution returns are independent.

[INSERT TABLE 5 HERE]

### *4.2 Evidence on systemic risk impacts of climate transition scenarios*

Using information from the bivariate copulas that characterize the market and the dependence structure for financial firms, for the sample period we compute the systemic risk impact for each financial firm arising from each climate transition scenario (hot house world, disorderly, and orderly transition). Specifically, at each time $t$ we compute the values for the systemic metrics reflected in Eqs. (1)-(3), i.e., CTER, CTVaR, and CTES, for confidence levels of $\alpha = 0.20$, $\beta = 0.20$, and $\gamma = 0.10$ and for quantiles $F_j(q_j^U) = 0.60$ and $F_j(q_j^L) = 0.40$ for $j = g, n, b$.[11]

### *4.2.1 Aggregate systemic risk impacts of climate transition scenarios*

Figure 4 depicts aggregate estimates of the three systemic metrics for the European financial system. As CTER is an additive measure, aggregated values are obtained as the weighted average of the individual values, weighted by the market value of each firm over the total market value of all financial firms. Since CTVaR and CTES are not additive measures, for each climate transition scenario we report median values along with 25% and 75% percentile values (represented by shaded areas).

[INSERT FIGURE 4 HERE]

Panel A in Figure 4 depicts CTER temporal dynamics, showing that the systemic impact on financial firms of a hot house world scenario is much more severe than the impact of orderly and disorderly transition scenarios; this impact was particularly evident during the COVID-19 pandemic period. This can be explained by varying financial firm exposure to brown and green assets, and by the fact that the pandemic shock has particularly hurt banks by increasing loan defaults in the housing and business sectors, by drops in the value of government bonds, and by increasing uncertainty about future economic activity. The (weekly) average loss corresponding to a hot house world scenario is about -1.3%, but is negligible for orderly and disorderly transition scenarios. The systemic impact dynamics of climate transition scenarios is revealed to oscillate over the sample period, with abrupt changes that reflect changes in the relative value of market assets, and with crises such as the COVID-19 pandemic noticeably widening the gap between the two extreme transition scenarios.

Panel B in Figure 4 depicts estimates for the CTVaR, likewise indicating greater losses in a hot house world scenario than in a disorderly transition scenario (with average weekly losses of -5.5% and -3.4%, respectively). While CTVaR median values in the three climate transition scenarios remain relatively stable over the sample period, they dropped abruptly with the outbreak of the COVID-19 pandemic, reflecting a risk increase in all scenarios and widening differences between the two extreme climate transitions scenarios (evidence consistent with the results for the CTER). Finally, fluctuations around median values are also greater in the hot

[11] Those confidence levels correspond to empirical quantiles for green, neutral, and brown weekly returns, respectively, as follows: $q_{0.2}$ =-1.27, -1.44, -1.99; $q_{0.4}^L$ = 0.21, -0.07, -0.19; $q_{0.6}^U$ = 0.87, 0.76, 0.75; $q_{0.8}$ =1.66, 1.58, 1.89.

house world scenario than in the other two scenarios, pointing to a more diverse impact of that scenario on financial institutions.

Panel C in Figure 4 yields evidence on tail losses that points to similar qualitative findings as for the CTVaR metric, with (weekly) average expected tail losses of -8.8% for a hot house world scenario and of around -6.2% for the disorderly and orderly transition scenarios. As with CTER and CTVaR, expected tail losses increased markedly with the outbreak of COVID-19. In addition, CTES dynamics in the hot house world scenario differs significantly from tail loss behaviour in the orderly and disorderly scenarios, which closely co-move.

Overall, evidence for the three systemic risk metrics point to the fact that impairment of the European financial system is sizeable in a hot house world transition scenario (brown (green) asset prices experience extreme upward (downward) movements), but relatively modest in a disorderly transition (green (brown) asset prices experience extreme upward (downward) movements) or in an orderly transition (green, neutral, and brown asset prices move around their median values).

#### *4.2.2 Systemic risk impacts of climate transition scenarios by financial firm types*

Figure 5 highlights dissimilar temporal dynamics patterns of the systemic risk impact of climate transition scenarios for different types of financial firms. For the CTER metric, Panel A in Figure 5 shows that the value of all financial firms deteriorates in a hot house world scenario. However, the decline in the $CTER$ value from a hot house world scenario is of lower size for banks (average value of -0.8%, receiving positive impacts at specific time periods), while real estate firms receive the largest impact (average value of -2.3%). This evidence is consistent with the diverse exposition of financial firms to different type of assets, where banks are more exposed to brown asset than real estate firms (see Figure 3); thereby the impact of a hot house world scenarios is more severe for real estate firms than for banks. In contrast, real estate firms and financial services firms are positively affected from a disorderly transition, while banks receive a negative impact and insurance companies a slightly positive impact. Not surprisingly, the effects of the COVID-19 pandemic are reflected in all transition scenarios, even though during that period the systemic impact from a disorderly transition scenario was less positive for banks than for the remaining firms. For all financial firms, the impact of an orderly transition scenario is negligible.

[INSERT FIGURE 5 HERE]

Interestingly, median values and it interquartile range of CTVaR represented in Panel B in Figure 5 also reflect the greater exposure of banks to brown assets, as the CTVaR estimates for banks in a hot house world scenario are higher (average value of -4.8%) than in a disorderly transition scenario (average value of -7.2%); this is due to the fact that banks are more positively impacted from upturns in brown asset prices than from upturns in green asset prices. Remarkably, the opposite is observed for insurance, financial services and real estate firms, where the value of CTVaR is higher in the disorderly transition scenario than in the hot house world scenario (e.g., for real estate firms average values of CTVaR are -2.2% and -5.5% in the former and latter scenarios, respectively).

Panel C in Figure 5 shows that expected tail losses for insurance, financial services and real estate firms are larger in a hot house world scenario that in a disorderly transition scenarios, and that the opposite occurs for banks. The temporal dynamics of the median CTES is similar to the dynamics of the CTVaR, with abrupt downward movement in the COVID-19 period.

All in all, evidence on the impact of different climate transition scenarios for different types of financial firms are not surprisingly consistent with the degree of exposition of those institution to changes in the green and brown asset prices. Table 6 presents a descriptive statistic for the three risk metrics under different scenarios by considering the whole set and different categories of financial firms as presented in Figures 4 and 5. Descriptive results confirm the above-described graphical evidence.

[INSERT TABLE 6 HERE]

Finally, we present evidence on the systemic impact of both hot house world and disorderly transition scenarios relative to the systemic effects of an orderly transition scenario. Figure 6 presents those relative effects for different financial firms groups and systemic risk measures. Panel A in Figure 6 evidence that, in terms of the CTER, a disorderly transition has more relative favourable effects for real estate and financial services firms than for banks or insurance companies. Similarly, evidence on the relative CTVaR presented in Panel B in Figure 6 also corroborates that the tail impact of a disorderly transition is greater for banks than for financial services and real estate firms, whereas for insurance firms that relative risk is rather similar in both transition scenarios. Consistently, relative expected tail losses in Panel C in Figure 6 confirm that relative expected tail losses for insurance, financial services and real estate firms are larger in the hot house world scenario than in the disorderly transition scenario, particularly with the outbreak of the pandemic, whereas relative differences for banks are narrower. Likewise, insurance, financial services and real estate firms are more heterogeneous in their exposure to a hot house world scenario than banks.

[INSERT FIGURE 6 HERE]

### *4.2.3 Systemic risk effects of climate transition scenarios for individual firms*

Table 7 presents average values over the sample period for the three systemic risk measures in the three climate transition scenarios for the four largest institutions within each category. The evidence in Table 7, consistent with the graphical evidence reported in Figure 3, is that financial institutions are diverse in terms of the impact of different scenarios.

Regarding the banking sector, the CTER, CTVaR, and CTES systemic risk metrics point to improved performance in a disorderly transition scenario and deteriorated performance in a hot house world scenario for the two largest banks, HSBC and BNP Paribas. In contrast, the systemic risk metrics for Santander and Intesa Sanpaolo banks, more exposed to brown than to green assets, deteriorate more in a disorderly transition scenario than in a hot house world scenario. This empirical evidence confirms that banks widely differ in terms of their exposure to climate risk, a fact that needs to be borne in mind in any regulation regarding that risk.

For the four largest insurance firms, the evidence indicates that CTER, CTVaR, and CTES average values are better for Alliance, Chubb and AXA in a disorderly transition scenario compared to a hot house world scenario, whereas the impact on Zurich of any of the three climate transition scenarios is fairly similar.

Finally, for the largest firms within the financial services and real estate categories, average CTER, CTVaR, and CTES values confirm enhanced performance in a disorderly transition scenario compared to a hot house world scenario. This finding, corroborating the evidence for the financial services and real estate firms overall, as presented in Figures 3 and 5, suggests that those firms, on the whole, are well positioned for transition to a low-carbon economy in which green (brown) firms would be revalued upwards (downwards).

[INSERT TABLE 7 HERE]

### *4.2.4 Systemic risk impact of climate transition scenarios for individual countries*

To explore systemic risk of climate stress scenarios for individual countries, for the CTER (additive) we compute average values for each financial institution in each country and aggregate those values using, as weights, the market value of each firm over the total market value of all financial firms in the corresponding country. For the CTVaR and CTES (nonadditive), we obtain the average value for each financial firm in each country over the sample period and take the median values of the averages as indicative of the VaR and ES.

Figure 7 depicts the systemic impact of the three climate transition scenarios on the European countries included in our sample. Panel A in Figure 7 shows that, in a disorderly transition scenario, the financial systems of Finland, France, and Norway benefit, given that their financial firms show higher (lower) exposure to green (brown) that to brown (green) assets. More specifically the average CTER values are higher than in other countries and CTVaR and CTES values also indicate better tail risk performance. In contrast, the financial systems of Ireland, Portugal, Poland and Spain are the countries most exposed to a disorderly transition, displaying the poorest performance in terms of the CTER, and also for tail risk, which is particularly high for the Italian financial system. Overall, most European countries show vulnerability to a disorderly transition scenario.

[INSERT FIGURE 7 HERE]

Regarding the hot house world scenario, Panel B in Figure 7 indicates that the financial systems of Portugal, Ireland, Luxembourg and Spain would benefit, increasing their average CTER and reducing lower tail risk in terms of the CTVaR and CTES with respect to other European countries. In contrast, the financial systems of Finland, France, and Norway show a poorer profile in terms of average returns and tail risk metrics.

Finally, for an orderly transition scenario, depicted in Panel C in Figure 7, the evidence points to the financial systems of Ireland and Portugal as the poorest performers in terms of the CTER and also in terms of tail risk, while the best performers in terms of tail risk are the financial systems of Finland, Switzerland, and Belgium.

Taken together, the overall picture of climate transition risk across European financial systems is very diverse, with countries ranking differently depending on the climate transition scenario.

## 5. Determinants of climate transition risk

Below we explore which individual characteristics of financial firms, markets, and macroeconomic information are associated with climate transition risks. As in previous research on systemic risk for financial institutions (e.g., Borri and Giorgio, 2021; Laeven et al., 2016), we consider: (a) balance sheet information such as size (measured as the log of total assets), leverage (assets to equity ratio) and return on assets (ROA), and (b) firm-specific market information as given by the price-to-book ratio and the $\beta$-CAPM (measured as the slope coefficient of the regression of financial firm returns on equity market returns). We also consider market features common for all financial firms, such as market volatility, market returns (measured by the European VIX index and STOXX Europe 600 returns, respectively), yield slope (the difference between 10- and 3-month sovereign German government bonds), and the default premium (the spread between Baa German corporate bonds and 10-year German government bonds). Finally, as general macroeconomic information for each country, we take annual industrial production growth, inflation, and unemployment gap.[12] Data was sourced from Bloomberg on annual basis, so the analysis for the CTER is annual (as the only additive systemic risk measure). Thus, for each financial firm $i$ the annual CTER is explained by the following panel regression model:

$$CTER_{i,t} = \alpha_i + \sum_{j=1}^{5} \beta_j X_{i,j,t-1} + \sum_{h=1}^{4} \lambda_h X_{h,t-1} + \sum_{k=1}^{3} \psi_k X_{i,k,t-1} + \varepsilon_{i,t} \tag{18}$$

where $\alpha_i$ denotes the financial firm fixed effects; $\beta_j$ are the coefficients that account for the marginal effects of the individual characteristics of financial firms on climate transition risks; $\lambda_h$ are the coefficients for financial market variables; and $\psi_k$ are the coefficients for the country macroeconomic variables. We also control for unobserved heterogeneity by including year fixed-effect dummies. We lagged all control variables to mitigate potential reverse causality concerns, and compute robust standard errors using double clustering at the firm and time levels (see Petersen, 2009).

Table 8 presents estimation results for the full sample and for the different financial firm types under different climate transition scenarios. For each scenario we report results from four regressions that individually consider variables for firm characteristics, market information, macroeconomic information, and finally, for all variables together.

Empirical evidence for the full sample in Panel A in Table 8 indicates that the impact of different variables varies depending on the climate transition scenario. For a disorderly climate transition, firm size reduces systemic impact, whereas leverage, the market returns, the yield slope and the default premium increase the systemic impact; this evidence corroborates other findings on the systemic impact of market distress scenarios (e.g., Borri and Giorgio, 2021; Laeven et al., 2016). In an orderly transition, leverage, ROA, price-to-book ratio, market return, VIX, yield slope, default premium, industrial production and inflation rates enhance transition

[12] The unemployment gap is calculated as difference between unemployment rate and non-accelerating inflation rate of unemployment (NAIRU) – data sourced from OECD Statistics. This measure is a thermometer on the labour market conditions (the labour market is rigid when unemployment rate is above NAIRU, otherwise there is spare capacity).

risk effects. Taken together, our evidence points to the relevance of firm-specific, market and macroeconomic information in shaping climate transition risk in a disorderly transition. As for the hot house world, the impact of different variables is insignificant, with the exception of ROA, default premium, yield slope industrial production and inflation. All in all, this evidence would suggest that climate transition risks in all scenarios are particularly driven by specific firm features, and market and macroeconomic information.

[INSERT TABLE 8 HERE]

Panels B (banks), C (insurance companies), D (financial services companies), and E (real estate companies) in Table 8 reveal that the effect of different variables on the dynamics of the transition risk widely differ across different firm types. Regarding banks, leverage reduces the CTER value in the disorderly transition scenario, but has no significant effects in other scenarios. The price-to-book reduces transition risk in the disorderly and orderly transition scenarios, while the effect of VIX is positive in a disorderly transition and negative in a hot house scenario. Evidence is mixed on the impact of macroeconomic variables on climate transition risk for banks, with inflation reducing systemic impacts in the disorderly and orderly transition scenario an increasing in the hot house scenario. Regarding insurance companies, leverage has negligible effects on the dynamics of climate transition risk, while the price-to-book ratio reduces systemic risk in a disorderly transition. The default premium has a negative impact on the CTER in the disorderly transition, but a positive impact in a hot house world scenario, whereas VIX and inflation rate information increases and increases transition risk in a disorderly transition, respectively. As for financial services companies, systemic risk dynamics is particularly shaped by market specific features such as the yield slope and the default premium, with opposite effects in the hot house and the orderly and disorderly scenarios, whereas leverage reduces the value of CTER in a disorderly transition. At the macro level, the unemployment gap significantly influences systemic risks in all scenarios. Finally, for real estate firms, ROA, market returns, yield slope, the default premium and inflation increase systemic risk in both the disorderly and orderly transition scenarios, while the remaining explanatory variables have no significant effect.

Overall, our evidence on determinants of climate transition risk points to the fact that financial firms are more sensitive to different economic determinants in a disorderly transition scenario than in an orderly or a hot house world scenario, and that the impact of those variables on systemic risk varies widely across financial firms.

## 6. Capital implications of climate transition risk

To assess the implication of each climate transition scenario in terms of capital shortfall for financial firms, following Brownlees and Engle (2017), we can define the climate transition capital shortfall (CTCS) for a financial institution *i* at time t as:

$$CTCS_{i,t} = kD_{i,t} - (1-k)\left(1 + LRCTER_{i,t}\right)W_{i,t}, \tag{19}$$

where $LRCTER_{i,t} = \exp\left(52 \cdot CTER_{i,t}\right) - 1$ is the one-year-ahead climate transition expected return, representing the expected change in equity under a specific climate transition stress scenario (computed as per Eq. (1) for a disorderly transition scenario), $k$ is the fraction of assets that the financial firm has to reserve in case of a crisis (the prudential capital ratio), $D_{i,t}$ is the debt book value, and $W_{i,t}$ is the equity market value. The CTCS, given by the difference between the required and available capital, is a forward-looking metric as it relies on the expected change in the market value of financial institution *i*. The dynamics of the CTCS is not only influenced by the climate transition scenario impact on returns, as given by the CTER, but also by the dynamics of market capitalization and debt. From the CTCS, we can define the climate transition systemic capital shortfall (CTRISK) for a financial institution *i* as a positive capital shortfall value:

$$CTRISK_{i,t} \ = \max\left\{0, CTCS_{i,t}\right\}. \tag{20}$$

Using information on the debt book value, market capitalization for each financial firm (sourced from Compustat), and CTER values (as reported in the previous section and expressed on an annual basis), we compute CTCS and CTRISK values for the different climate transition scenarios considering a capital ratio of $k = 5.5\%$.[13] Figure 8 represents the dynamics of the total CTRISK value for the four most impacted firms and the remaining firms within each category, showing that capital shortfall differs across financial firms and over time.

[INSERT FIGURE 8 HERE]

Banks experience substantial capital shortfalls from a disorderly transition scenario, at average values of about 40 billion euros, peaking at 120 billion euros during a high-risk period (such as the COVID-19 pandemic). Substantial differences exist between banks, with the four most impacted banks accounting for a small fraction of the total capital shortfall. For those banks, Table 9 presents average CTRISK values, indicating that, in a disorderly transition scenario, the most impacted banks, excepting Santander, experience average capital shortfalls

[13] This ratio, also used by Engle et al. (2014) for European financial firms, ensures no capital shortfall for a leverage of 18.2.

that represent an important fraction of their market capitalization. In contrast, in a hot house world scenario, and even though average values for total CTRISK are quite similar to those for a disorderly transition scenario, there is great dispersion between banks, with the most four impacted banks accounting for a large fraction of the total CTRISK value — mainly Credit Agricole (average CTRISK value representing 65% of its market capitalization). The capital impact of an orderly transition scenario is moderate, with average values of around 5 billion euros, and concentrated in the most affected banks, with capital shortfalls representing a small fraction of their market capitalization. Overall, the empirical estimates point to a relatively manageable impact on bank capital of climate transition in comparison with a financial crisis, when capital consumption is substantially greater; see, e.g., Engle et al. (2014) who report an average capital shortfall in a financial crisis of around 400 billion euros for European banks). The effects of climate transition in terms of positive capital shortfalls are concentrated in a small number of entities, and interestingly, as the average CTCS value is below zero, those positive capital shortfalls are absorbable by the banking sector.

[INSERT TABLE 9 HERE]

For insurance companies, capital shortfall estimates, depicted in Figure 8, show that they are barely affected in the orderly and disorderly transition scenarios, except during the COVID-19 pandemic, when capital shortfall peaks at 1 billion euros. However, capital shortfall is mostly affected in a hot house world scenario. Table 9 evidences that capital losses for insurance firms are concentrated in a small number of firms and mainly affected by the hot house world scenario, overall representing a small percentage of their market capitalization.

Regarding financial services, Figure 8 shows that firms are particularly affected in a hot house world scenario, with average capital shortfall over the sample period of 15 billion euros; this figure is reduced by half in a disorderly transition scenario and shrinks to less than 1 billion euros in an orderly transition scenario. As for insurance firms, Table 9 indicates that capital shortfalls for the most impacted financial service firms represent a small fraction of their market capitalization, with the exception of Deutsche Bank AG in the disorderly transition scenario.

Finally, Figure 8 shows that capital shortfalls for real estate firms are negligible in the disorderly and orderly transition scenarios, and although larger in a hot house overall, as reported in Table 9, capital shortfalls represent a small fraction of firm capitalization. This evidence is consistent with the greater unfavourable impact on real estate firms of a hot house world scenario.

Figure 9 represents the impact of climate transition risks on capital shortfalls across countries as given by total CTRISK, showing that countries react differently to alternative climate transition scenarios. Thus, Germany, Italy, and Spain need to assume greater capital shortfalls in a disorderly transition scenario; France, United Kingdom, and Switzerland in a hot house world scenario; and Italy, Germany, and France in an orderly transition scenario.

[INSERT FIGURE 9 HERE]

## 7. Prospective climate transition risk impacts

To assess how climate transition scenarios could impair future financial firm returns, we consider a forward-looking period of five years, simulating the dependence structure for the market and financial firm *i* (as represented in Figure 1) over the next *T*+*h* periods, with *h* = 1,…, 260 weeks. Each simulation *s* = 1,…*S*, where *S* denotes the total number of simulations, is performed in two steps: we first simulate the market structure (as represented in the upper panel in Figure 1), which is common to all the financial institutions, and we then simulate the dependence structure for each financial firm *i* with the market (as represented in the lower panel in Figure 1).

In the first step, at time *T*+*h* we use information up to *T*+*h*-*1* within each simulation to update the copula parameters for the three bivariate copulas, $C_{gn}(u_g, u_n; \theta^{(s)}_{gn,T+h})$, $C_{bn}(u_b, u_n; \theta^{(s)}_{bn,T+h})$, and $C_{gb|n}(u_g|u_n, u_b|u_n; \theta^{(s)}_{gb|n,T+h})$, where $\theta^{(s)}_{gn,T+h}$, $\theta^{(s)}_{bn,T+h}$ and $\theta^{(s)}_{gb|n,T+h}$ denote the respective copula parameters. These parameters may change according to the dynamics indicated in Table 1, or may remain stable if the estimated copulas are static ($\theta_{gn,T+h} = \theta_{gn,T}$, $\theta_{bn,T+h} = \theta_{bn,T}$ and $\theta_{gb|n,T+h} = \theta_{gb|n,T}$). We next draw a sample *s* from the C-vine structure to obtain $u^{(s)}_{g,T+h}$, $u^{(s)}_{n,T+h}$ and $u^{(s)}_{b,T+h}$ using the algorithm in Aas et al. (2009),[14] and use this information to update copula parameters for the period *T*+*h*+*1* in each simulation path.

In the second step, we simulate the dependence structure for each financial institution *i* with the market at time *T*+*h* as follows. To simulate $u^{(s)}_{i,T+h}$ given the market information on $u^{(s)}_{g,T+h}$, $u^{(s)}_{n,T+h}$ and $u^{(s)}_{b,T+h}$, we need the conditional copula $C_{i|b,g,n}\left(u_i \middle| u^{(s)}_{g,T+h}, u^{(s)}_{n,T+h}, u^{(s)}_{b,T+h}\right)$. This copula derives from the joint copula density of institution *i* and the market as:

[14] A detailed explanation of the simulation of the C-vine structure is provided in Appendix B.

$$C_{i|b,g,n}\left(u_i \middle| u_{g,T+h}^{(s)}, u_{n,T+h}^{(s)}, u_{b,T+h}^{(s)}\right) = \frac{\int_0^{u_i} c\left(v_i, u_{g,T+h}^{(s)}, u_{n,T+h}^{(s)}, u_{b,T+h}^{(s)}\right) dv_i}{\int_0^1 c\left(v_i, u_{g,T+h}^{(s)}, u_{n,T+h}^{(s)}, u_{b,T+h}^{(s)}\right) dv_i} \quad (21)$$

where $c(\cdot)$ denotes the copula density.[15] To simulate $u_{i,T+h}^{(s)}$, we sample a uniform variable $\xi$ on [0,1], with the simulated value of $u_{i,T+h}^{(s)}$ solving $C_{i|b,g,n}\left(u_{i,T+h}^{(s)} \middle| u_{g,T+h}^{(s)}, u_{n,T+h}^{(s)}, u_{b,T+h}^{(s)}\right) = \xi$.

The values for $CTER_{i.T+h}^{(s)}$, $CTVaR_{i,T+h}^{(s)}$ and $CTES_{i,T+h}^{(s)}$ can be computed from Eqs. (8)-(15) using information on the conditional copulas at time $T+h$, and information on the return distribution of the financial institution, $F_i^{(s)}(\cdot)$. The parameters that characterize that distribution are $\lambda_i$ and $\nu_i$, which remain constant over time, and $\sigma_{i,T+h}^{2(s)}$ and $\mu_{i,T+h}^{(s)}$, which fluctuate with changes in the dynamics given by the ARMA-GARCH model of returns for financial institution *i*. The values of those two last parameters are obtained from the simulated value of $u_{i,T+h}^{(s)}$ by plugging $\sigma_{i,T+h}^{2(s)} \bar{F}_i^{-1}(u_{i,T+h}^{(s)})$ as $\epsilon_{i,T+h}$ in Eq. (16) — to obtain $\mu_{i,T+h}^{(s)}$ from the ARMA(p,q) structure for p or q higher than zero — and again in Eq. (17) — to obtain $\sigma_{i,T+h+1}^{2(s+1)}$, where $\bar{F}_i^{-1}$ denotes the inverse of the standardized skewed t of financial institution *i* with parameters $\lambda_i$ and $\nu_i$. Finally, from the set of S simulations we obtain the simulated value of the three systemic risk metrics as: $CTER_{i,T+h} = \frac{1}{S}\sum_{s=1}^{S} CTER_{i.T+h}^{(s)}$, $CTVaR_{i,T+h} = \frac{1}{S}\sum_{s=1}^{S} CTVaR_{i,T+h}^{(s)}$, and $CTES_{i,T+h} = \frac{1}{S}\sum_{s=1}^{S} CTES_{i,T+h}^{(s)}$. Similarly, we can aggregate the CTER by category *G* as $CTER_{g,T+h} = \frac{1}{S}\sum_{s=1}^{S}\sum_{i\in G} \omega_i\, CTER_{i.T+h}^{(s)}$ and obtain confidence intervals as $CTER_{\alpha,g,T+h} = min\left\{CTER_{g.T+h}^{j} \,\middle|\, \frac{1}{S}\sum_{s=1}^{S} 1_{CTER_{g.T+h}^{(s)} \leq CTER_{g.T+h}^{j}} \geq \alpha \right\}$, where $1_A$ is one if A holds and zero otherwise.

Figure 10 depicts simulated evidence on the impact of the three climate transition scenarios on the financial stability of financial firms, as given by the CTER and its 5% and 95% percentile values over five years for $S = 1000$ simulations. For the full set of European financial firms, prospective evidence from Panel A in Figure 10 points to aggregate differences between scenarios. The hot house world scenario causes drawdowns in return values that remain relatively stable over the simulated period. Financial firms achieve very small return gains in a disorderly transition scenario, particularly uncertain in the first years of the simulated period but later stabilizing. An orderly transition scenario implies a negligible impact for financial firms. Note that, as reflected by the 5% and 95% percentiles, there is a wide diversity between

[15] The expression for copula density is reported in Appendix C.

financial firms regarding the impact of different climate transition scenarios, but especially of the hot house world scenario.

[INSERT FIGURE 10 HERE]

Panel B in Figure 10 reveals that sensitivity to climate transition risks varies across different types of financial firms. Banks can be expected to be placed at a significant disadvantage in a disorderly transition scenario, but are likely to be positively affected in a hot house world scenario, and to receive modest impacts in an orderly transition. Insurance firms can expect similarly moderate systemic risk impacts in the disorderly and orderly transition scenarios, but negative in a hot house world scenario. Financial services and especially real estate firms are likely to experience significant systemic risk effects in the hot house world scenario, but clearly improved returns in the disorderly and orderly transition scenarios. Overall, this evidence is consistent with the evidence reported for the in-sample period.

## 8. Conclusions

Moving towards a greener economy involves risks for the value of financial assets, with repricing effects (Carney, 2016) potentially having an impact on the stability of financial systems. In this paper, we describe an empirical setup with the aim of quantifying the systemic impact of climate transition risks on financial firms. Our proposal is based on featuring the conditional distribution of financial firm returns, considering, as conditional variables, market returns for green, neutral, and brown assets, reflecting low, neutral, and high vulnerability, respectively, to transition to a low-carbon economy. We characterize the conditional distribution of financial firm returns in three climate transition scenarios (hot house world, orderly transition, and disorderly transition) in terms of relative changes in green, neutral, and brown return, and assess the systemic impact of each scenario in terms of $\mathrm{CTER}$, $\mathrm{CTVaR}$, and $\mathrm{CTES}$ values.

We apply our methodology to European financial firms (banks, insurance companies, financial services companies, and real estate firms) over the period 2013-2020. Our main findings are that the systemic impact of climate transition scenarios varies widely across financial institutions. Banks experience more systemic impacts in the disorderly transition scenario than in the hot house world scenario, while the opposite occurs for the other financial firm types, but especially for real estate firms. We also find that the systemic impact of the different climate transition scenarios is widely divergent within financial firm types (mainly within the bank group), yielding potential winners and losers, and also in terms of the impact on financial systems in different European countries.

The implications of this study go beyond risk management, as it provides a useful methodology for generating stress test scenarios for climate risk. Regulatory and supervisory authorities might also find in this study a flexible tool to evaluate the performance of financial firms under different distress scenarios coherent with the transition to a low-carbon economy, and that takes into account financial fears in the market through non-linearities and tail dependencies.

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**Figure 1.** Dependence structure between market and financial institution returns.

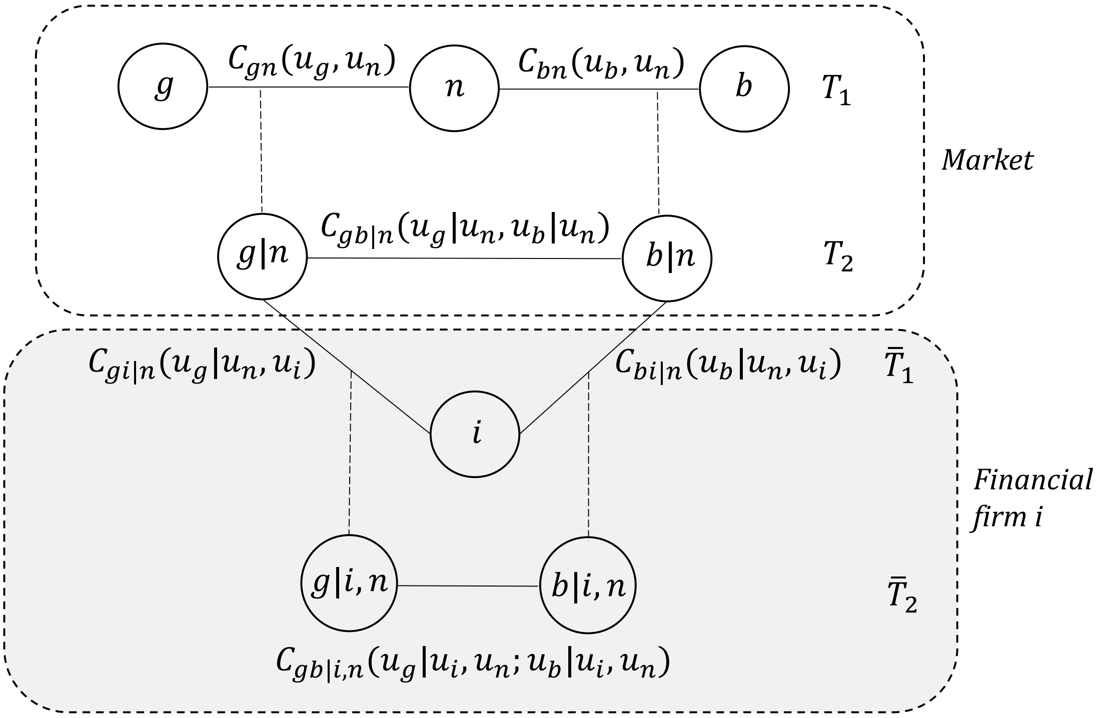


**Figure 2.** Cumulative returns for different asset classes and financial institutions.

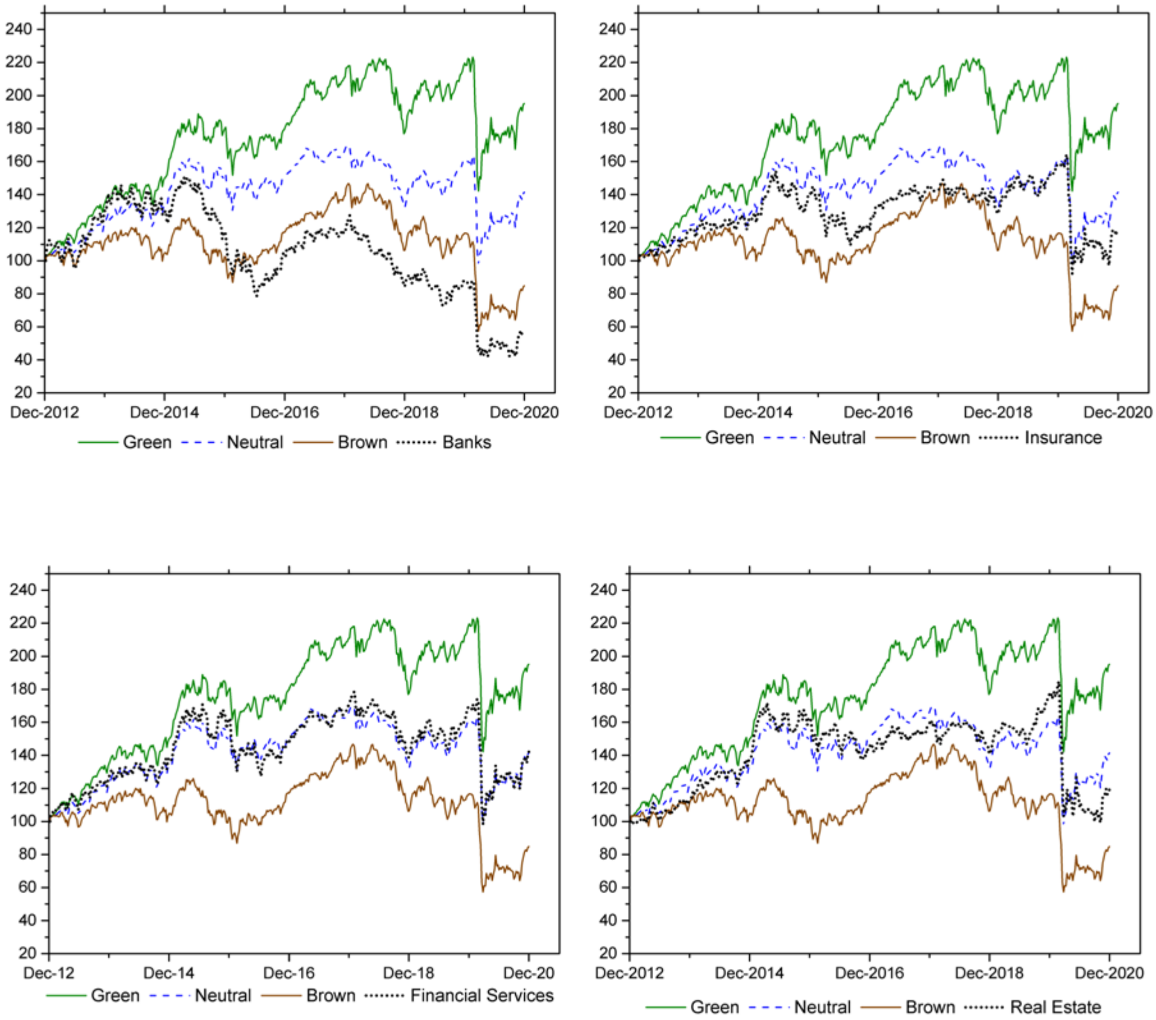
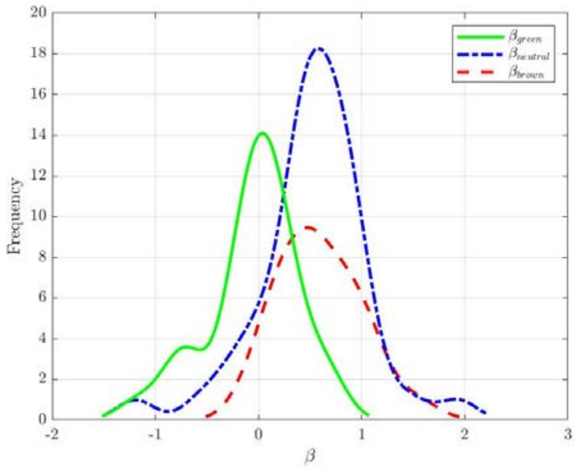


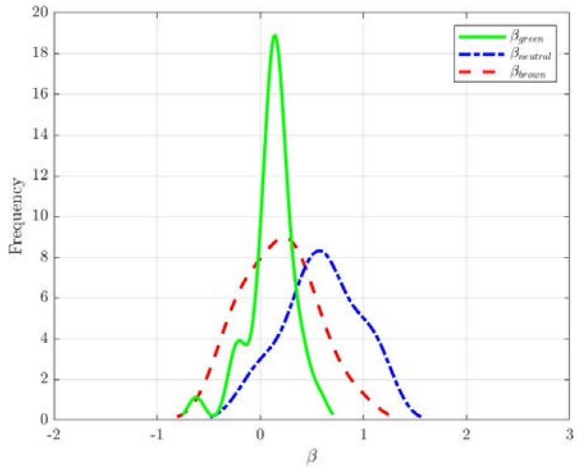
**Figure 3.** Exposure of financial firms to green, neutral, and brown asset returns.

**Panel A.** Distribution of beta values for green, neutral, and asset returns.

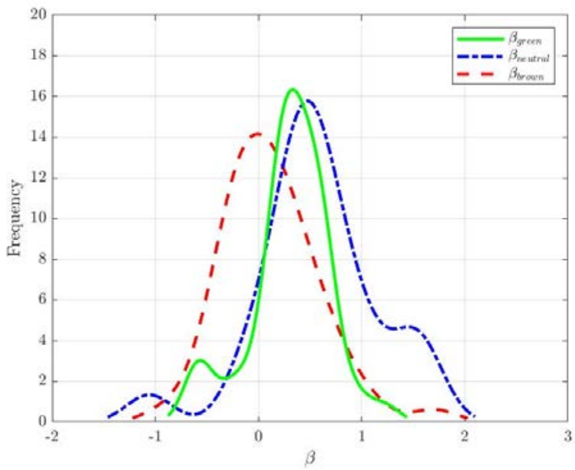
Banks



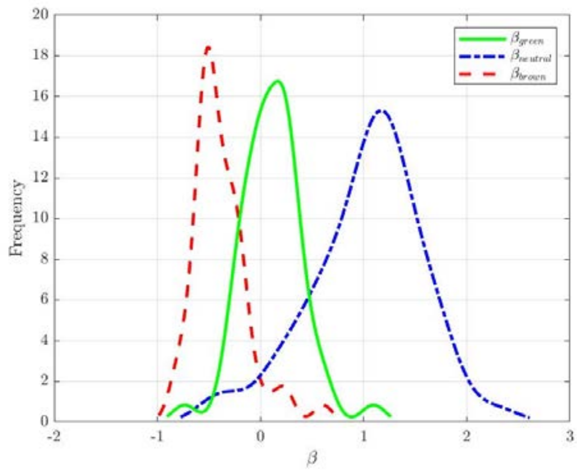

Insurance companies




Financial services

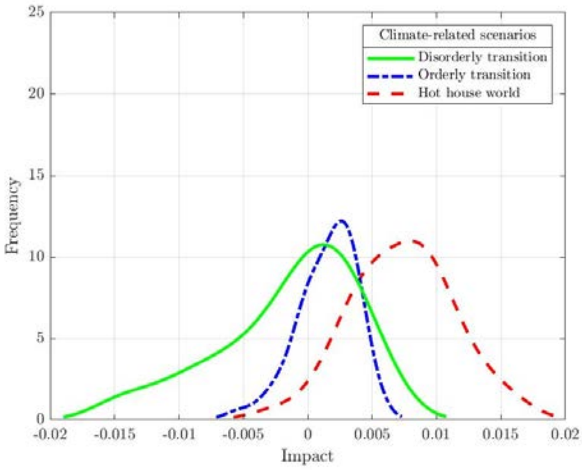



Real estate

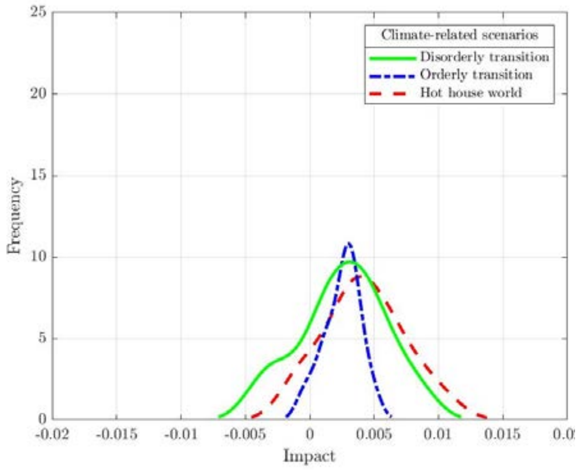


**Panel B.** Distribution of average return impacts under different climate transition scenarios.

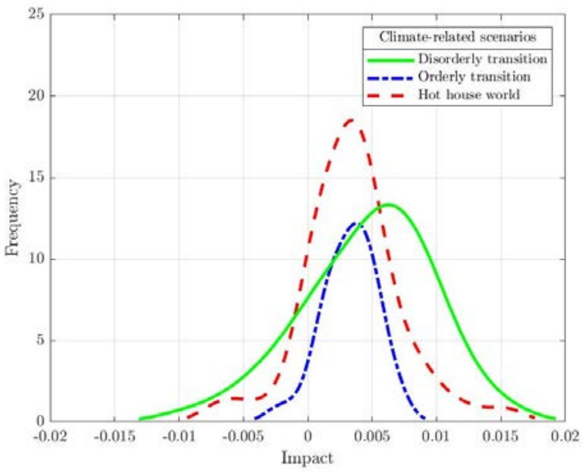
Banks




Insurance companies




Financial services




Real estate

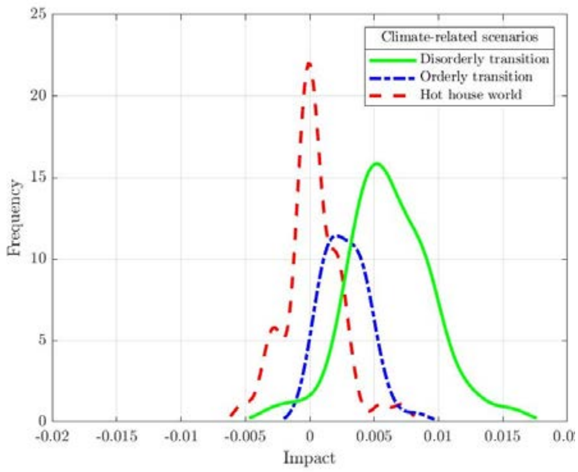
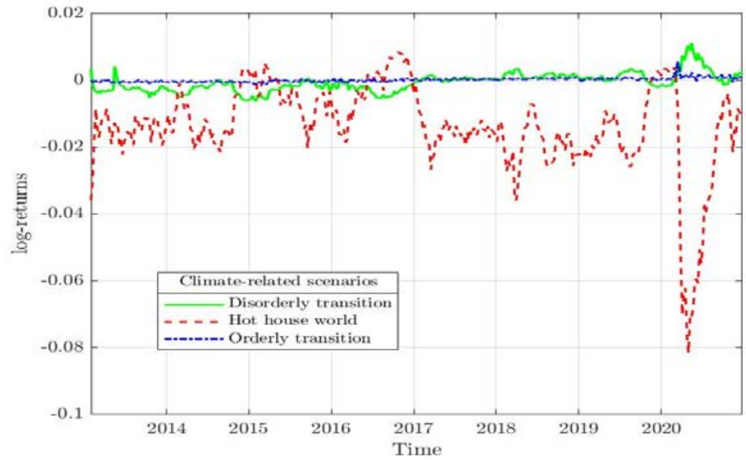
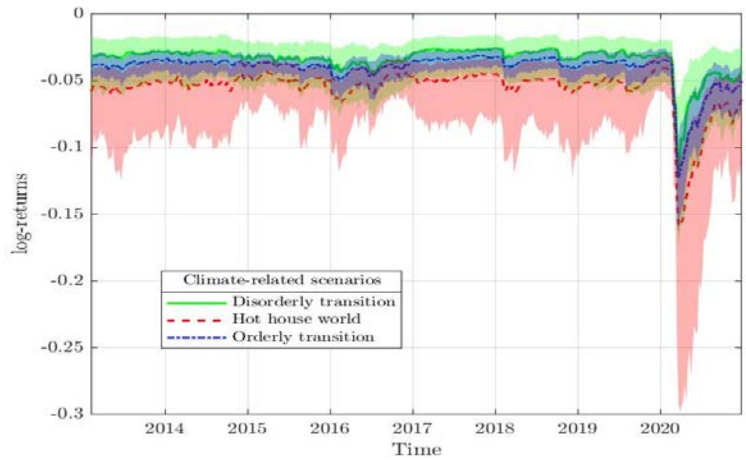


**Figure 4.** Systemic risk of climate transition scenarios for the financial system.

**Panel A.** CTER




**Panel B.** CTVaR




**Panel C.** CTES

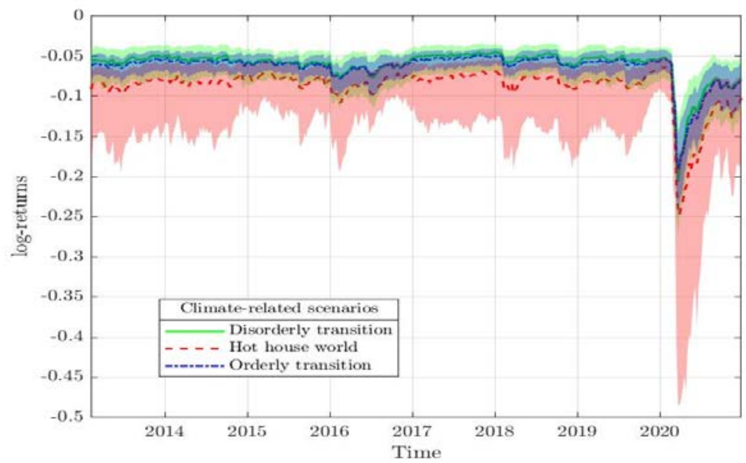
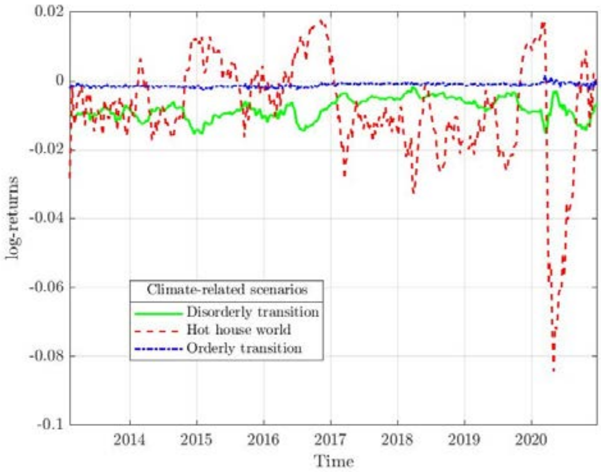


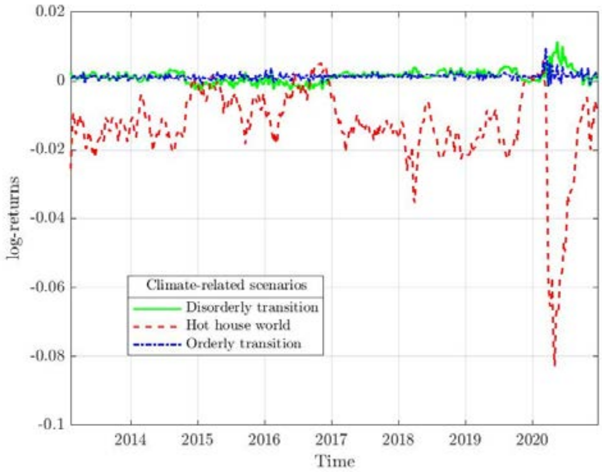
**Figure 5.** Systemic risk of climate transition scenarios for different financial firm types.

**Panel A.** CTER

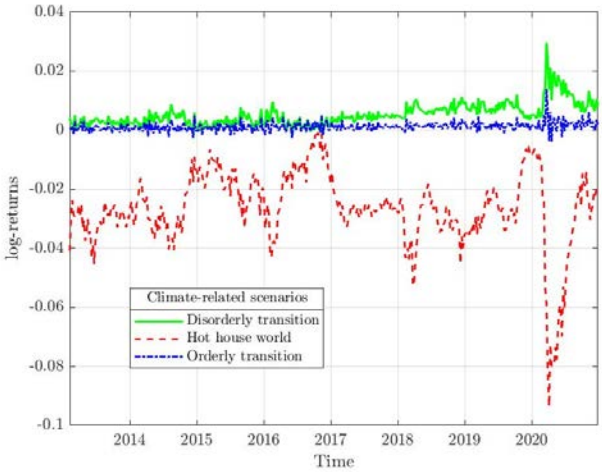
Banks



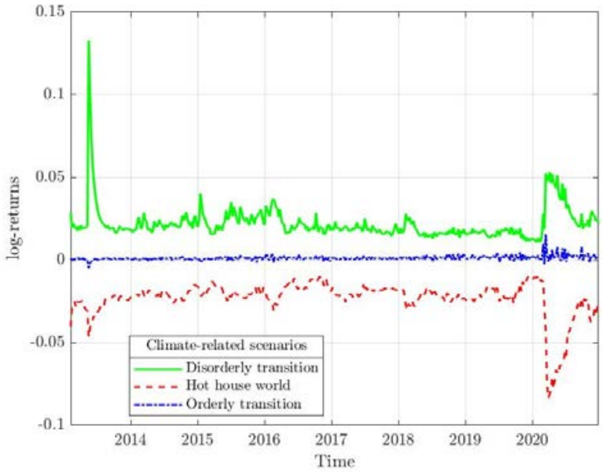

Insurance companies




Financial services

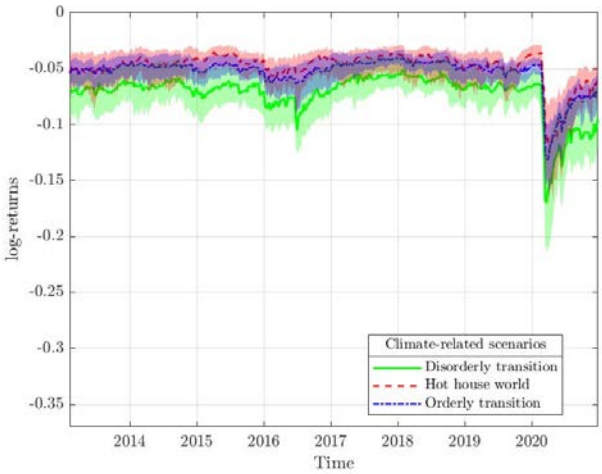



Real estate

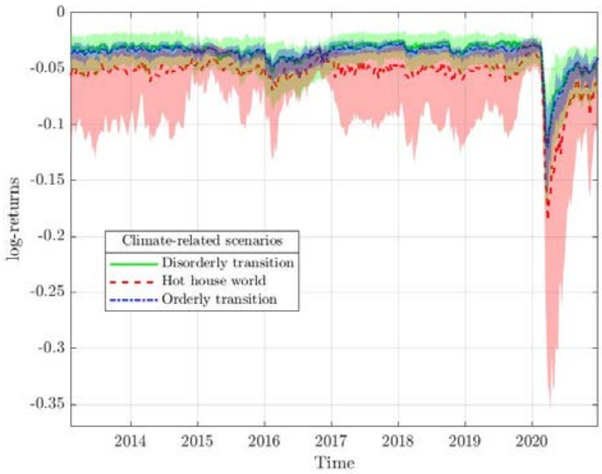


**Panel B.** CTVaR

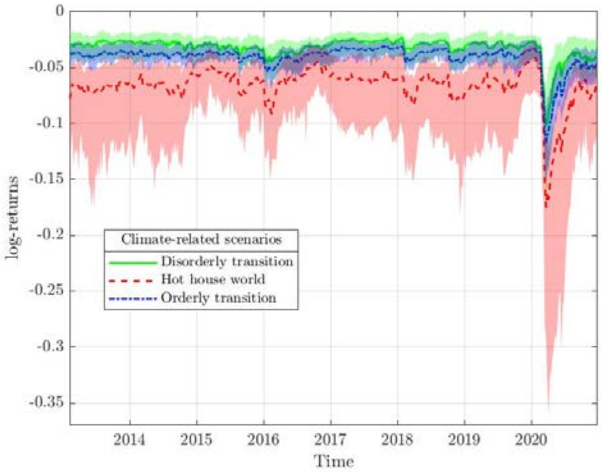
Banks



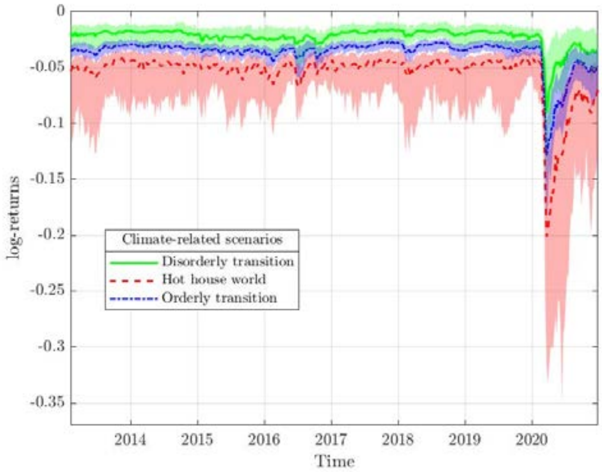

Insurance companies




Financial services

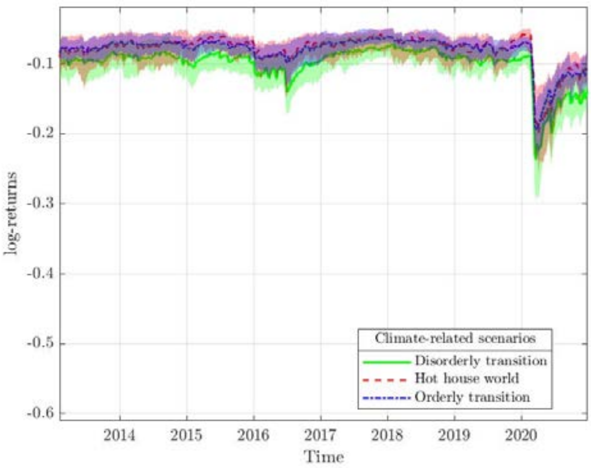



Real estate

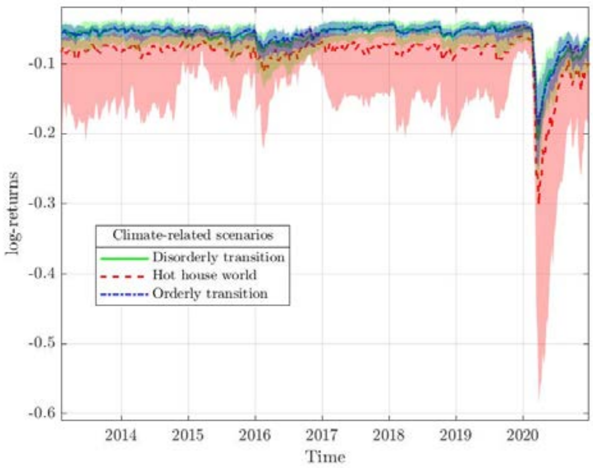


**Panel C.** CTES

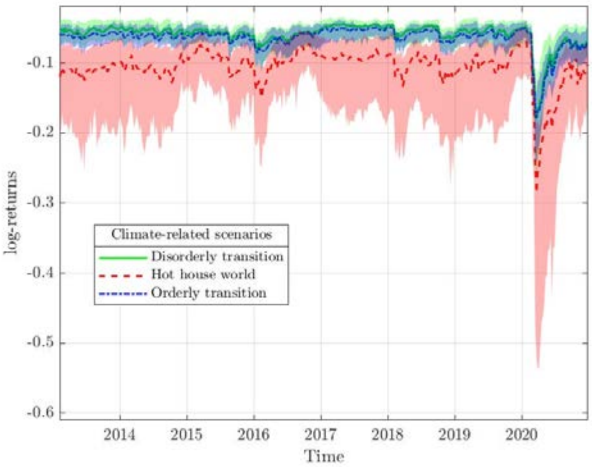
Banks




Insurance companies




Financial services




Real estate

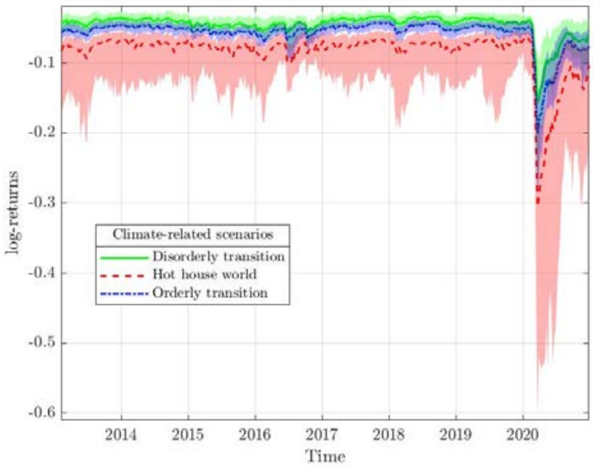
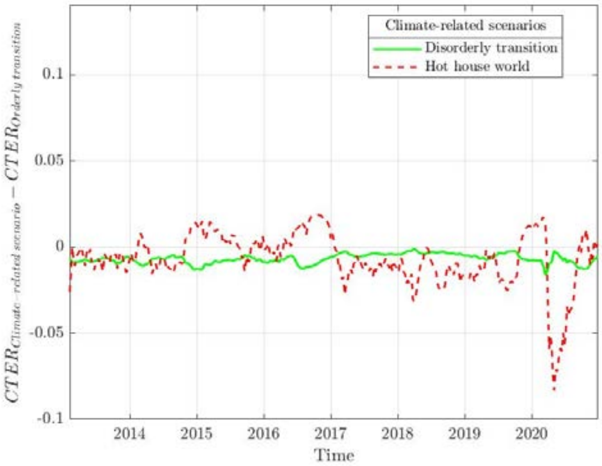


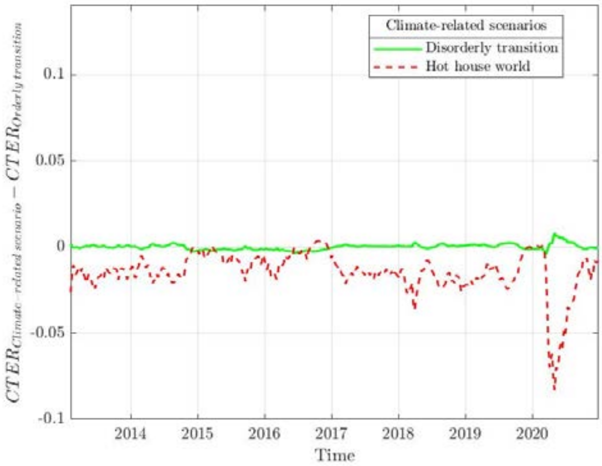
**Figure 6.** Relative systemic risk of climate transition scenarios by financial firm types.

**Panel A.** CTER

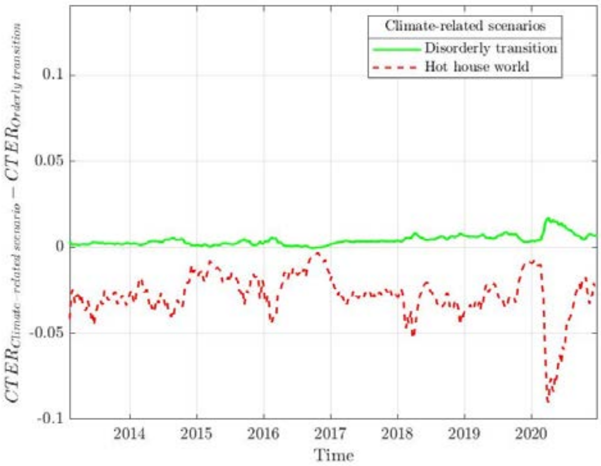
Banks



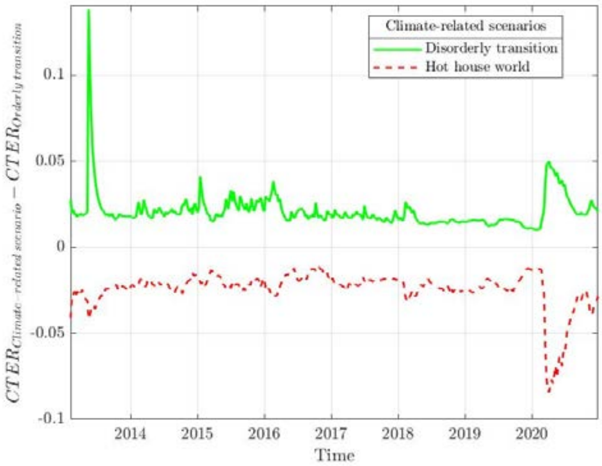

Insurance companies




Financial services

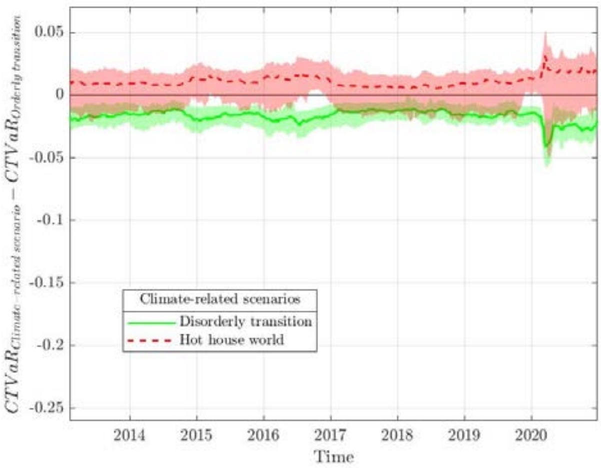



Real estate

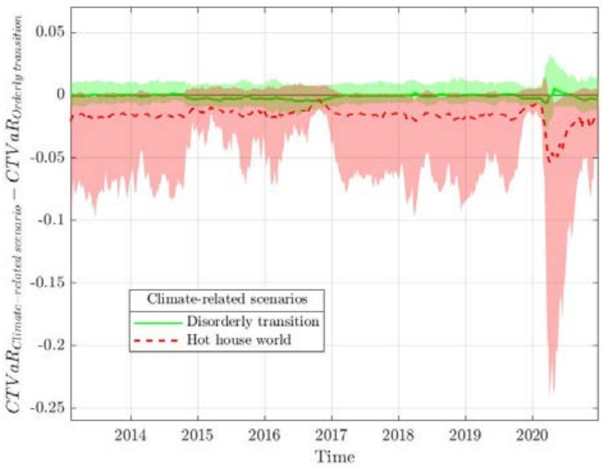


**Panel B.** CTVaR

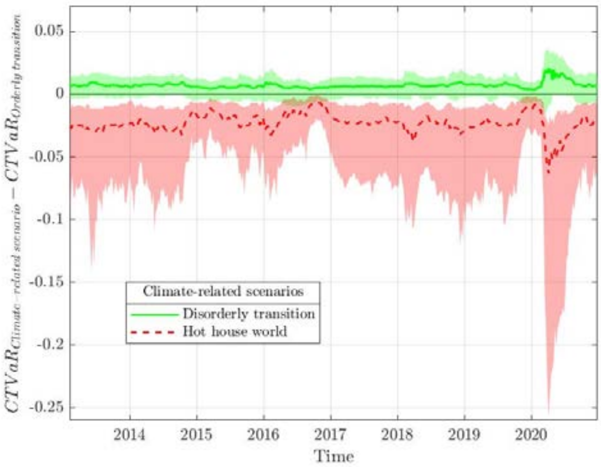
Banks



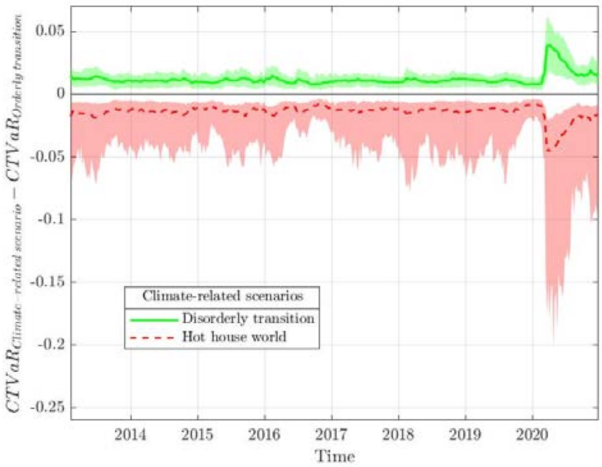

Insurance companies




Financial services

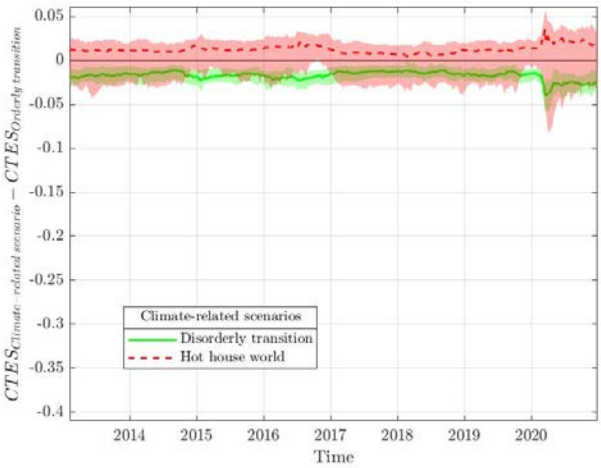



Real estate

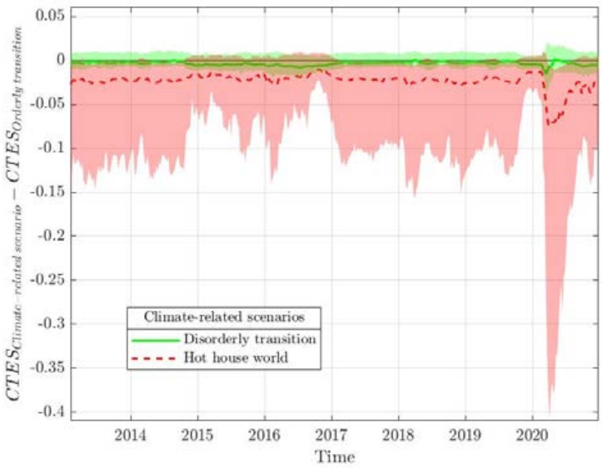


**Panel C.** CTES

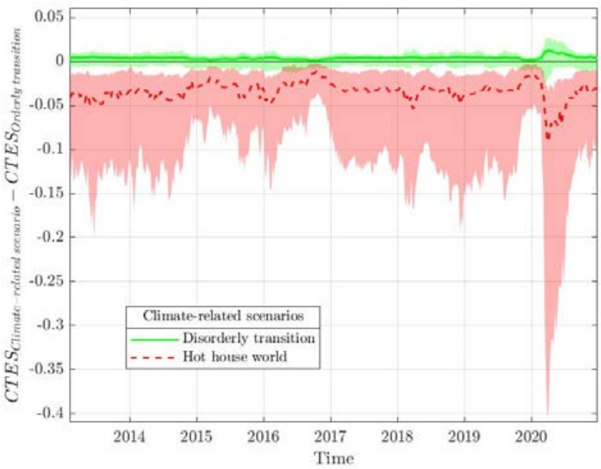
Banks




Insurance companies




Financial services




Real estate

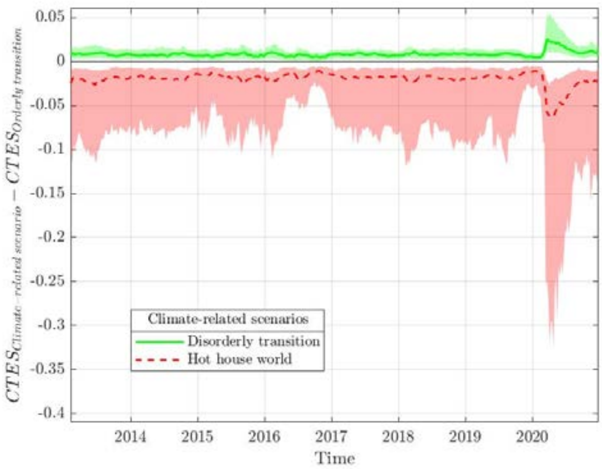
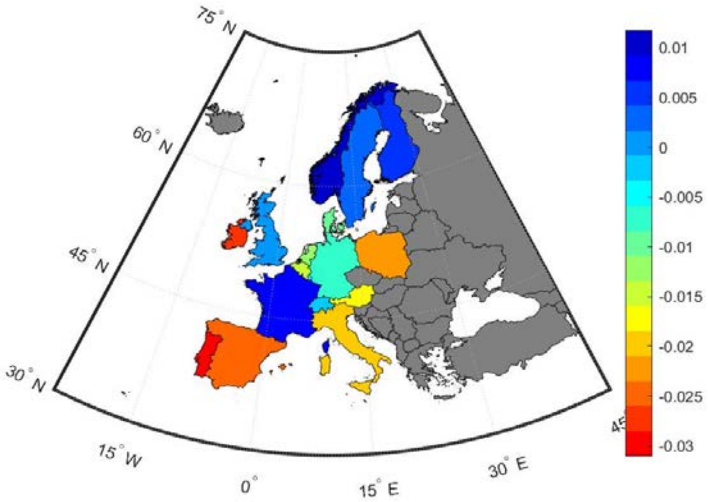


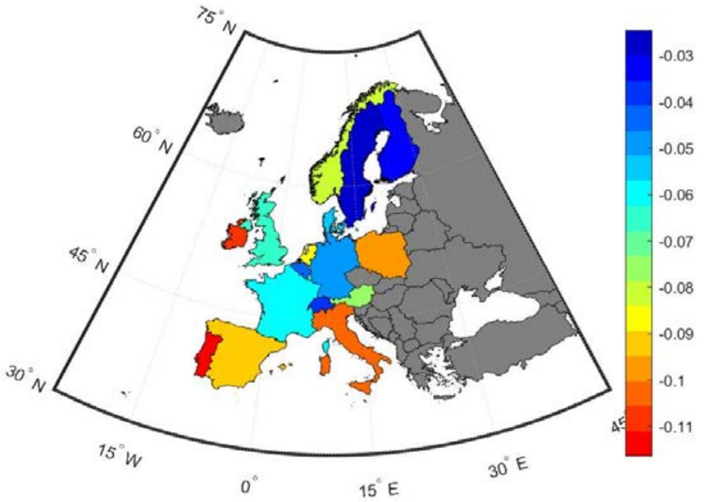
**Figure 7.** Systemic risk of climate transition scenarios by countries.

**Panel A.** Disorderly transition scenario

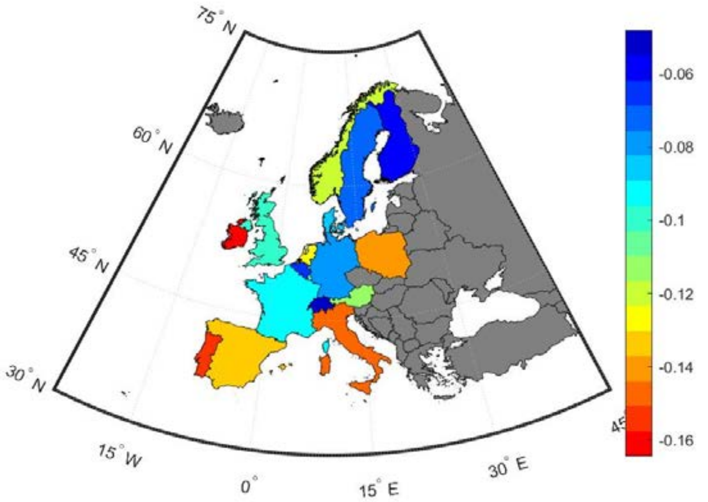
CTER




CTVaR

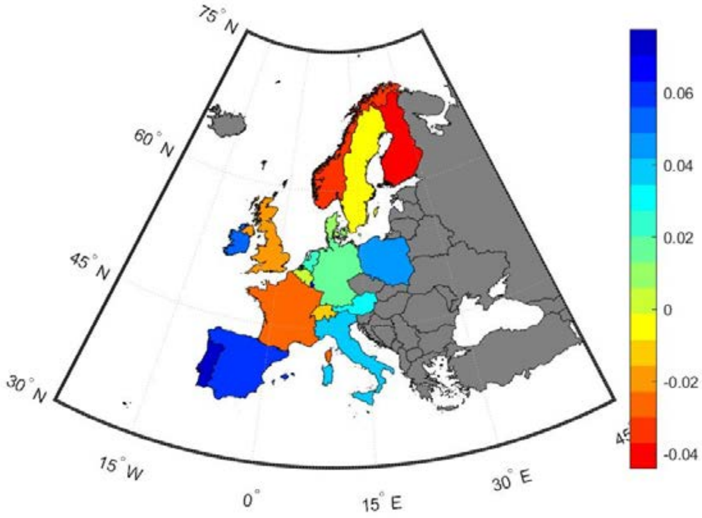



CTES

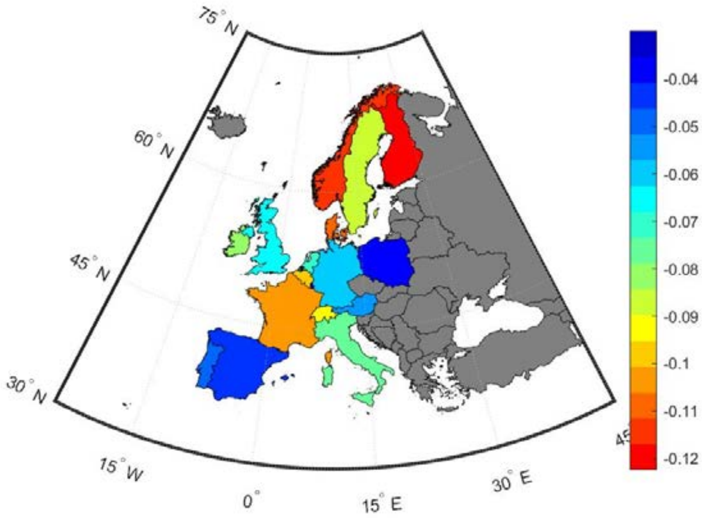


**Panel B.** Hot house world scenario

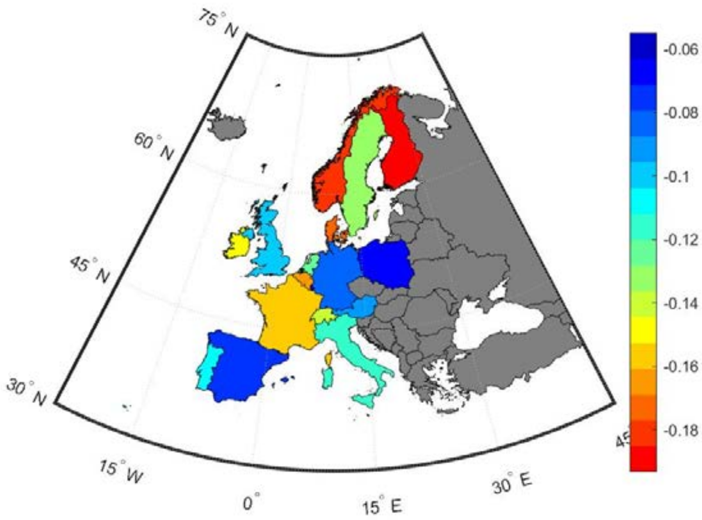
CTER




CTVaR

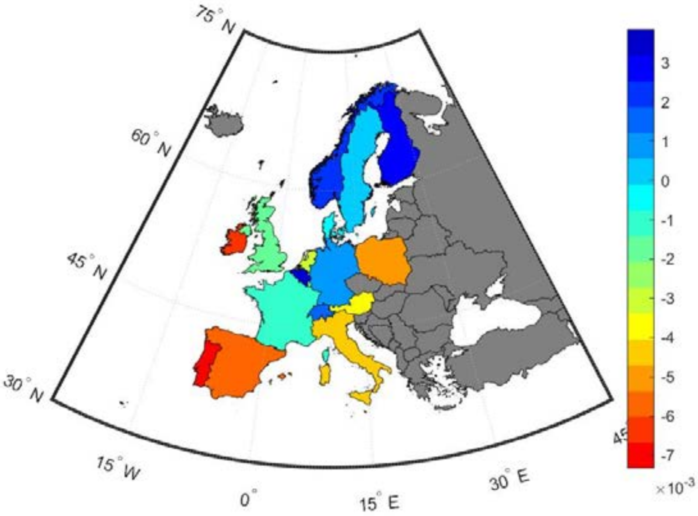



CTES

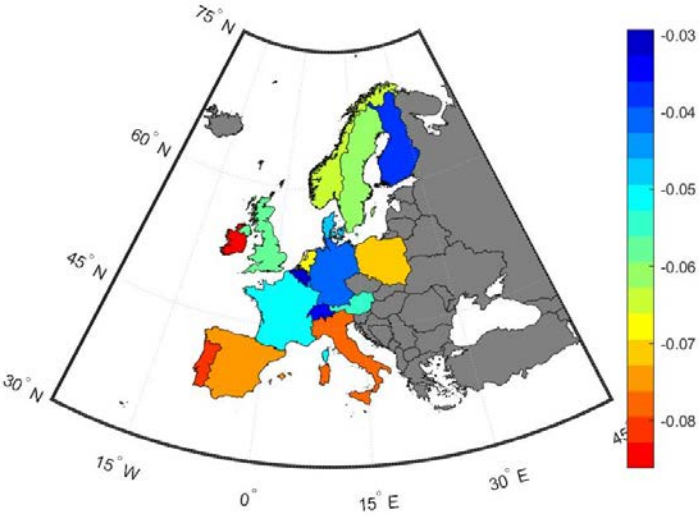


**Panel C.** Orderly transition scenario

CTER




CTVaR




CTES

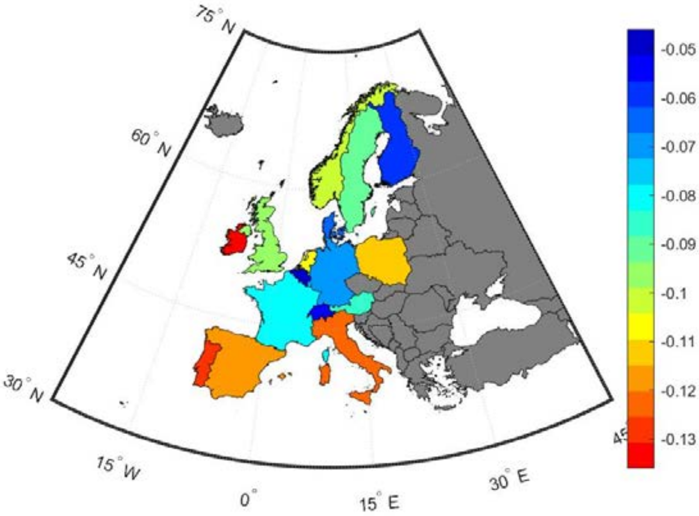
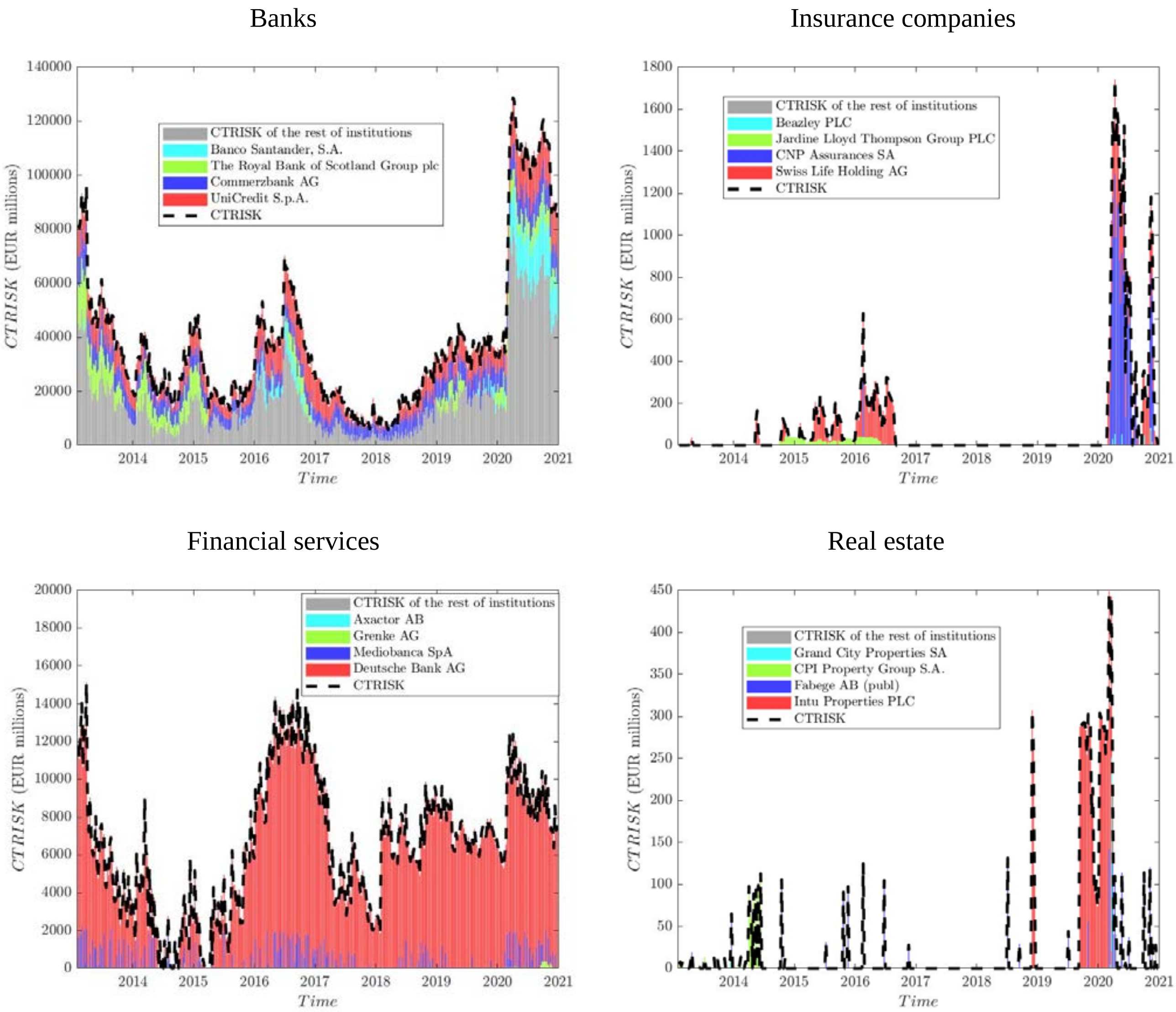


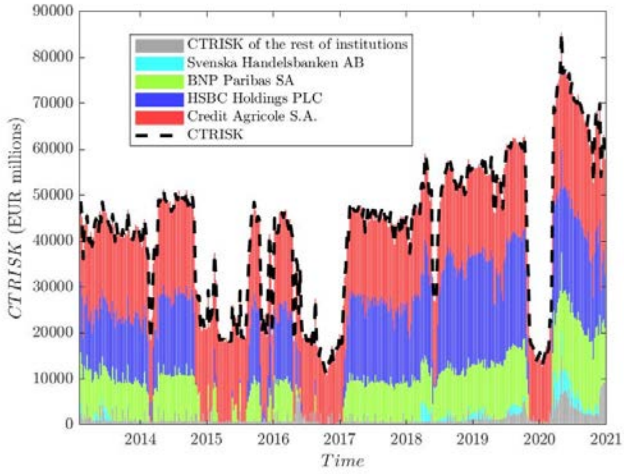
**Figure 8.** Capital shortfall from climate transition scenarios for financial institution types.

**Panel A.** Disorderly transition

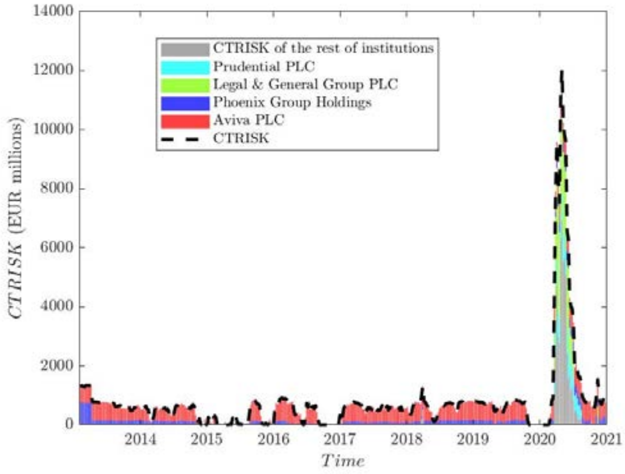


**Panel B.** Hot house world

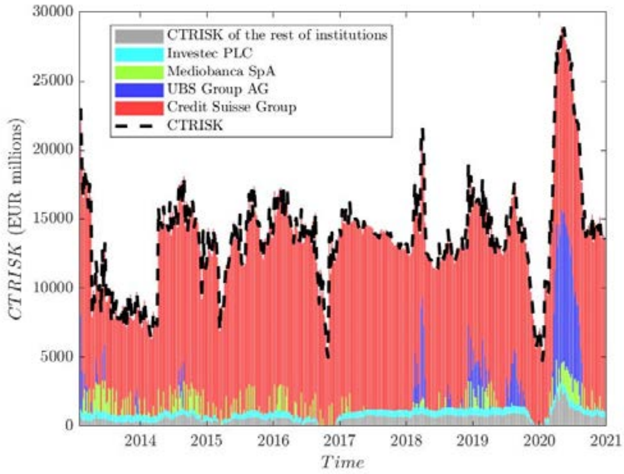
Banks



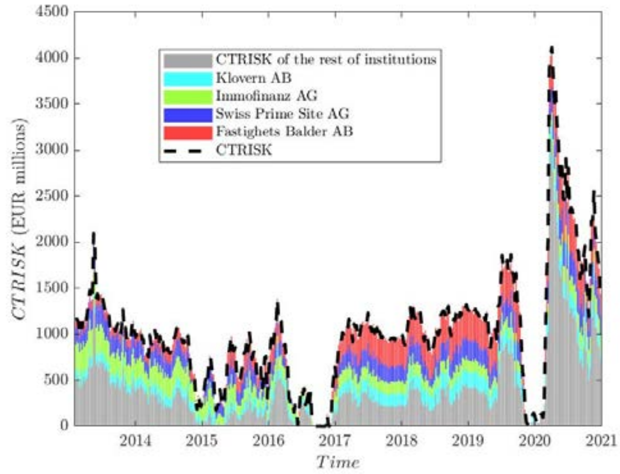

Insurance companies




Financial services

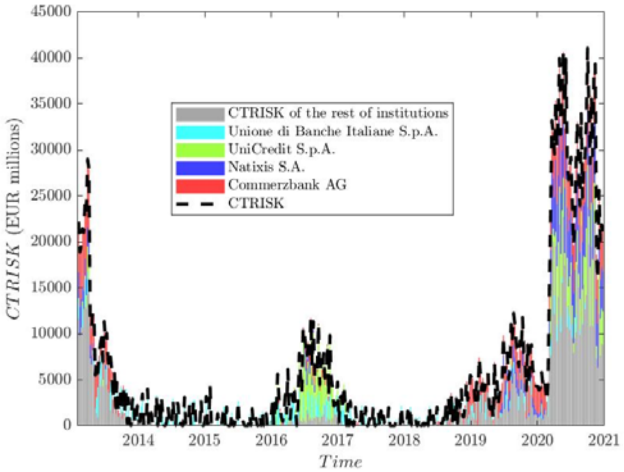



Real estate

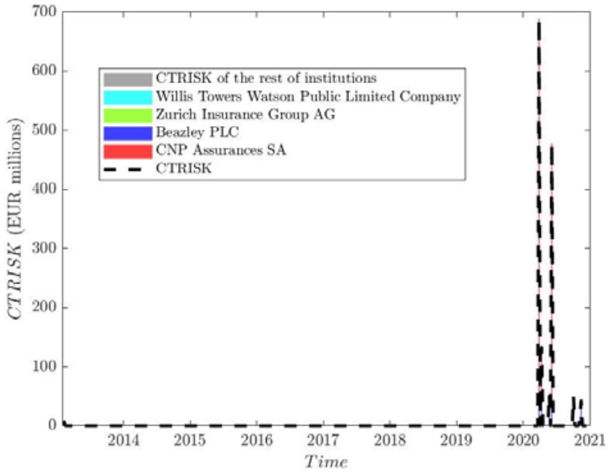


**Panel C.** Orderly transition

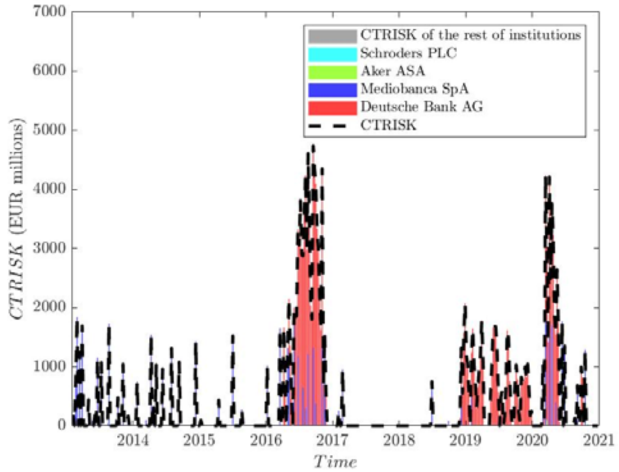
Banks




Insurance companies




Financial services




Real estate

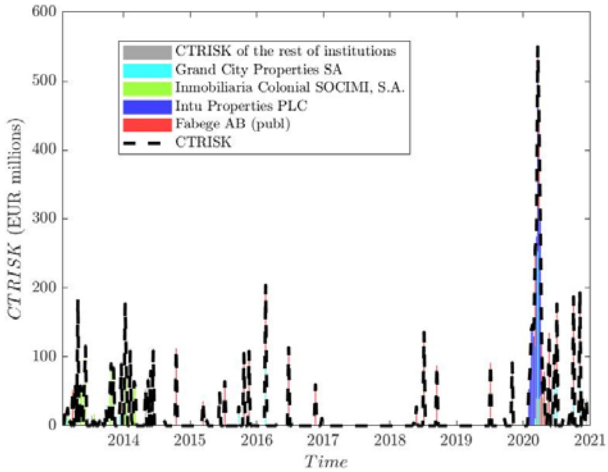
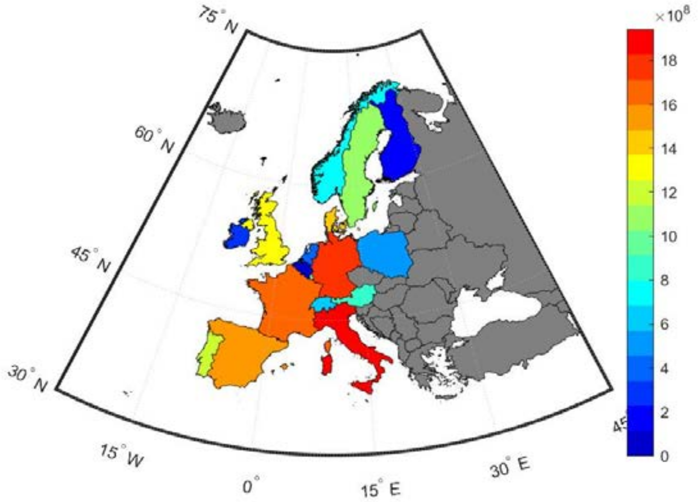
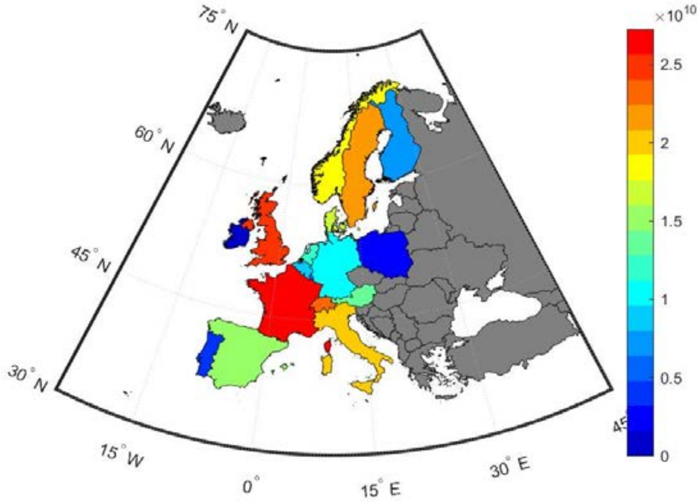


**Figure 9.** Capital shortfall (CTRISK) from climate transition scenarios by countries.

**Panel A.** Disorderly transition scenario




**Panel B.** Hot house world scenario




**Panel C.** Orderly transition scenario

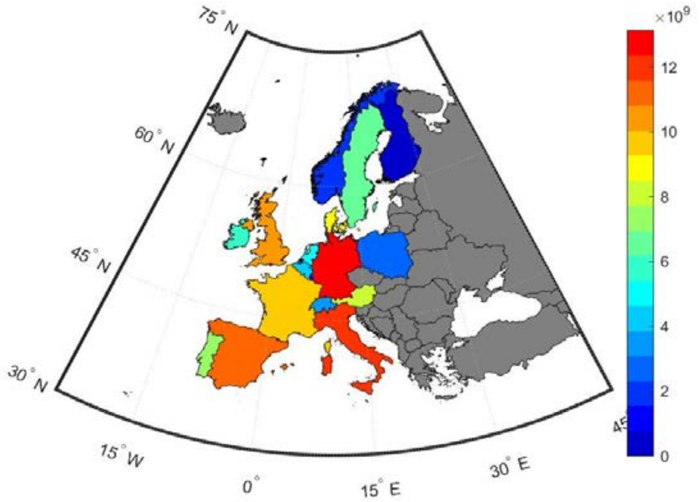
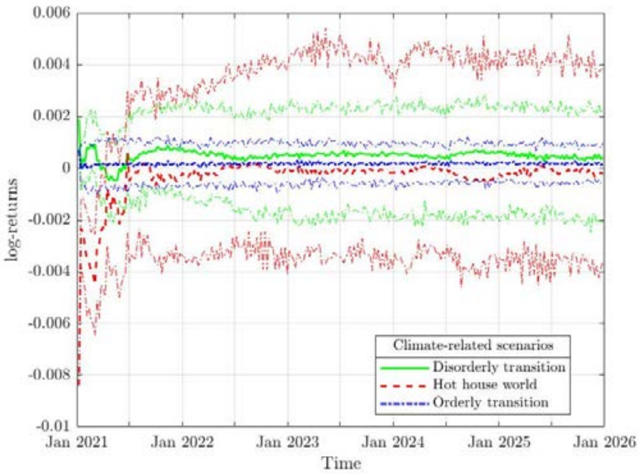


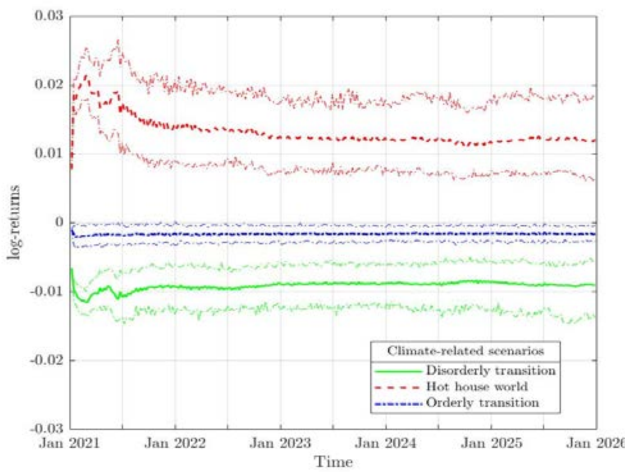
**Figure 10.** Simulated CTER value over five years under different climate transition scenarios.

**Panel A.** European financial system

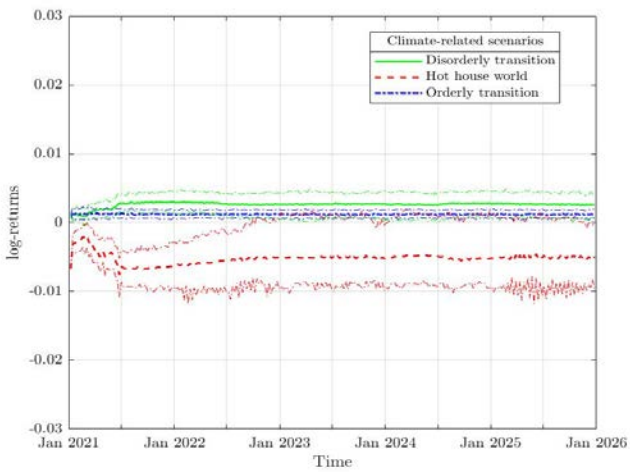



**Panel B.** Financial institution types

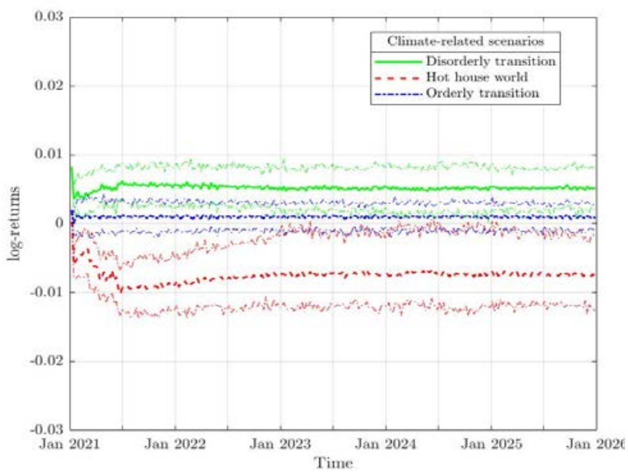
Banks




Insurance companies




Financial services




Real estate

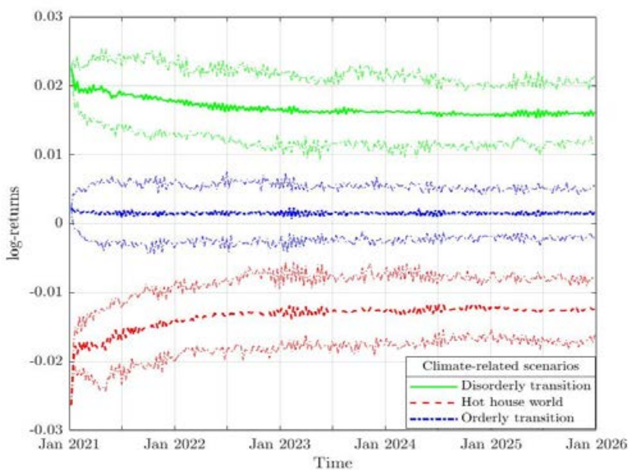


**Table 1.** Bivariate copula models.

| Name | Copula specification | Parameter | Tail dependence |
|---|---|---|---|
| Independent | $u_1 u_2$ | — | — |
| Gaussian | $\Phi(\Phi^{-1}(u_1), \Phi^{-1}(u_2); \rho)$ | $\rho$ | No tail dependence: $\lambda_U = \lambda_L = 0$ |
| Student t | $T_\eta\left(T_\eta^{-1}(u_1), T_\eta^{-1}(u_2); \eta, \rho\right)$ | $\rho, \eta$ | Symmetric tail dependence: $\lambda_L = \lambda_U = 2t_{\eta+1}\left(-\sqrt{(\eta+1)(1-\rho)/(1+\rho)}\right)$ |
| Clayton | $\left(u_1^{-\theta} + u_2^{-\theta} - 1\right)^{-\frac{1}{\theta}}$ | $\theta$ | $\lambda_L = 2^{-\frac{1}{\theta}}$, $\lambda_U = 0$ |
| Gumbel | $\exp\left(-\left(\left(-\log(u_1)\right)^{\theta} + \left(-\log(u_2)\right)^{\theta}\right)^{\frac{1}{\theta}}\right)$ | $\theta$ | $\lambda_L = 0$, $\lambda_U = 2 - 2^{\frac{1}{\theta}}$ |
| BB1 | $\left(1 + \left(\left(u_1^{-\theta} - 1\right)^{\delta} + \left(u_2^{-\theta} - 1\right)^{\delta}\right)^{\frac{1}{\delta}}\right)^{-\frac{1}{\theta}}$ | $\theta, \delta$ | $\lambda_L = 2^{-\frac{1}{\theta\delta}}$, $\lambda_U = 2 - 2^{\frac{1}{\delta}}$ |

**Note.** $\lambda_U$ ($\lambda_L$). denotes upper (lower) tail dependence. Time-varying dependence is assumed by allowing parameters to change over time, with dynamics given by an ARMA(1,q)-type process (Patton, 2006) for the linear dependence parameter of the Gaussian and Student-t copulas, given by $\rho_t = \Lambda_1\left(\psi_0 + \psi_1 \rho_{t-1} + \psi_2 \frac{1}{q}\sum_{j=1}^{q} \Phi^{-1}(u_{t-j})\Phi^{-1}(v_{t-j})\right)$, where $\Lambda_1(x) = \frac{1-\exp(-x)}{1+\exp(-x)}$ is the modified logistic transformation that keeps the value of $\rho_t$ in (-1,1), and where $\Phi^{-1}(x)$ is the standard normal quantile function ($\Phi^{-1}(x)$ is replaced by $T_\eta^{-1}(x)$ for the Student-t copula). For the parameters of the Clayton, Gumbel, and BB1 copulas, we assume that the dynamics is given by : $\theta_t = \Lambda_2\left(\bar{\omega}_\theta + \bar{\beta}_\theta \theta_{t-1} + \bar{\alpha}_\theta \frac{1}{q}\sum_{j=1}^{q} |u_{t-j} - v_{t-j}|\right)$ (in the same way for $\delta$ the BB1 copula), where — as in Patton (2006) — q is set to 26 and $\Lambda_2(x) = \frac{100}{1+\exp(-x)}$ for the Clayton copula, $\Lambda_2(x) = 1 + \frac{99}{1+\exp(-x)}$ for the Gumbel copula, and $\Lambda_2(x) = \frac{1}{1+\exp(-x)}$ for the BB1 copula. We also use 90º rotated copulas for the Clayton, Gumbel, and BB1 to allow for negative dependence. The 90º rotated copula is expressed as $C_{90}(u_1, u_2) = u_2 - C(1 - u_1, u_2)$ where $C(\cdot,\cdot)$ is the corresponding standard copula.

**Table 2.** Summary statistics for returns of different asset classes and of financial firms.

| | Market assets | | | Financial firms | | | |
|---|---|---|---|---|---|---|---|
| | Green | Neutral | Brown | Banks | Insurance companies | Financial services | Real estate |
| Return | 0.19% | 0.12% | 0.01% | -0.07% | 0.08% | 0.12% | 0.08% |
| Volatility | 2.34% | 2.51% | 3.09% | 5.19% | 3.81% | 4.17% | 4.08% |
| Skewness | -1.821 | -2.025 | -1.544 | -0.613 | -0.620 | -0.773 | -0.650 |
| Kurtosis | 16.393 | 20.259 | 17.005 | 11.299 | 12.789 | 12.706 | 18.605 |
| Max. downturn | -19.27% | -22.27% | -26.00% | -32.46% | -24.49% | -26.86% | -28.86% |
| Max. upturn | 10.33% | 11.02% | 12.73% | 23.83% | 18.56% | 19.44% | 22.28% |
| 1st quartile | -0.83% | -0.90% | -1.45% | -2.69% | -1.69% | -1.86% | -1.69% |
| 3rd quartile | 1.39% | 1.36% | 1.59% | 2.73% | 2.05% | 2.31% | 2.01% |
| 10% (left) VaR | -2.81% | -3.09% | -3.94% | -6.72% | -4.80% | -5.22% | -5.14% |
| 10% (left) ES | -3.92% | -4.28% | -5.41% | -9.18% | -6.60% | -7.20% | -7.07% |
| 10% (right) VaR | 3.19% | 3.33% | 3.97% | 6.59% | 4.96% | 5.47% | 5.30% |
| 10% (right) ES | 4.30% | 4.51% | 5.43% | 9.04% | 6.76% | 7.45% | 7.23% |

**Note.** This table presents summary statistics for weekly returns in euros for green, neutral, and brown assets and for European financial firms over the sample period January 2013 to December 2020. For each asset category, we report the average returns, volatility, skewness, kurtosis, maximum downturn and upturn, 10% value-at-risk (VaR), and expected shortfall (ES) for the left and right sides of the return distribution.

**Table 3.** Maximum likelihood parameter estimates of marginal models.

| | Market assets | | | Financial firms | | | |
|---|---|---|---|---|---|---|---|
| | Green | Neutral | Brown | Banks | Insurance companies | Financial services | Real Estate |
| **Mean** | | | | | | | |
| $\phi_0$ | 0.002* | 0.000 | -0.001 | -0.001 | 0.001 | 0.001 | 0.001 |
| | (0.00) | (0.01) | (0.00) | | | | |
| $\phi_1$ | | -0.411 | | 0.045 | -0.023 | -0.054 | -0.064 |
| | | (0.92) | | | | | |
| $\varphi_1$ | | 0.111* | | -0.085 | 0.091 | -0.102 | -0.093 |
| | | (0.03) | | | | | |
| **Volatility dynamics** | | | | | | | |
| $\omega$ | 0.000* | 0.000* | 0.000* | 0.000 | 0.000 | 0.000 | 0.000 |
| | (0.00) | (0.07) | (0.00) | | | | |
| $\alpha_1$ | 0.086* | 0.012* | 0.013* | 0.107 | 0.085 | 0.089 | 0.149 |
| | (0.07) | (0.01) | (0.09) | | | | |
| $\beta_1$ | 0.656* | 0.697* | 0.795* | 0.724 | 0.668 | 0.664 | 0.636 |
| | (0.32) | (0.20) | (0.40) | | | | |
| $\delta_1$ | 0.241* | 0.229* | 0.190* | 0.038 | 0.067 | 0.052 | 0.043 |
| | (0.08) | (0.11) | (0.13) | | | | |
| **Skewed t distribution** | | | | | | | |
| $\lambda$ | -0.407* | -0.399* | -0.315* | -0.091 | -0.123 | -0.104 | -0.064 |
| | (0.05) | (0.05) | (0.06) | | | | |
| $\vartheta$ | 5.692* | 5.607* | 7.148* | 10.067 | 6.201 | 5.356 | 5.739 |
| | (1.28) | (3.23) | (2.12) | | | | |
| **Goodness of fit** | | | | | | | |
| LogLik | -1078.41 | -1047.99 | -968.76 | -713.51 | -816.15 | -848.26 | -854.06 |
| LJ | [0.67] | [0.98] | [0.71] | [0.65] | [0.61] | [0.60] | [0.62] |
| LJ2 | [0.78] | [0.97] | [0.52] | [0.47] | [0.58] | [0.47] | [0.47] |
| ARCH-LM | [0.98] | [0.99] | [0.97] | [0.57] | [0.67] | [0.65] | [0.69] |
| K-S | [0.84] | [0.78] | [0.89] | [0.89] | [0.88] | [0.90] | [0.88] |

**Notes.** This table presents parameter estimates of the marginal models for market assets (categorized as green, neutral, and brown) and for European financial firms (banks, insurance companies, financial services, and real estate) as per Eqs. (16)-(17). For markets assets, the z-statistic for the parameter estimates is reported in brackets, whereas parameter estimates for financial firms are the average of the parameter estimates for each financial firm. For asset markets, an asterisk denotes statistical significance at the 5% level. LogLik, LJ, and LJ2 denote the log-likelihood value of the marginal model, Ljung-Box statistics for serial correlation in the model residuals and in the squared model residuals, respectively, computed with 20 lags. ARCH effects in the residuals are tested up to 20$^{th}$ order using Engle's Lagrange multiplier (ARCH-LM) test. KS denotes the Kolmogorov-Smirnov statistic for the null hypothesis of correct model specification (p values in square brackets). For financial institutions, goodness-of-fit information is the average of that information from all marginal models.

**Table 4.** Parameter estimates of bivariate copula models for green, neutral, and brown market assets.

| | Copula model | Parameter estimates | AIC |
|---|---|---|---|
| $C_{gn}(u_g, u_n)$ | BB1 | $\hat{\theta} = 1.986^{*}$ (0.21) | -794.82 |
| | | $\hat{\delta} = 1.885^{*}$ (0.12) | |
| $C_{bn}(u_b, u_n)$ | BB1 | $\overline{\omega}_{\theta} = 2.554$ (3.58) | -741.48 |
| | | $\overline{\alpha}_{\theta} = -9.695$ (18.38) | |
| | | $\overline{\beta}_{\theta} = 0.294$ (0.71) | |
| | | $\overline{\omega}_{\delta} = -2.214^{*}$ (0.18) | |
| | | $\overline{\alpha}_{\delta} = 1.029$ (2.29) | |
| | | $\overline{\beta}_{\delta} = 4.232^{*}$ (0.22) | |
| $C_{gb\|n}(u_g\|u_n, u_b\|u_n)$ | Independent | — | 0 |

**Note.** This table presents parameter estimates of the best copula fit for the copula models in Table 1 for pairings of green, neutral, and brown returns as represented in the upper panel in Figure 1. Standard errors were computed through simulation. An asterisk indicates significance of the parameter at the 1% level. The minimum AIC value adjusted for small-sample bias is reported in the last column.

**Table 5.** Summary of the bivariate copula models for financial firms.

| | Copula model | % institutions | Summary of parameter estimates |
|---|---|---|---|
| $C_{gi\|n}(u_g\|u_n, u_i)$ | Gaussian | 35.8 | $\hat{\rho} = 0.13$ [0.10, 0.18] |
| | Student-t | 2.6 | $\hat{\rho} = 0.16$ [0.08, 0.24]<br>$\hat{\upsilon} = 26.33$ [9.95, 50.93] |
| | Clayton | 33.7 | $\hat{\theta} = 0.46$ [0.24, 0.68] |
| | 90-Clayton | 0.5 | $\hat{\theta} = 0.64$ [0.64, 0.64] |
| | Gumbel | 4.7 | $\hat{\theta} = 1.11$ [1.04,1.18] |
| | 90-Gumbel | 0.5 | $\hat{\theta} = 1.16$ [1.16,1.16] |
| | Independent | 22.2 | — |
| $C_{bi\|n}(u_b\|u_n, u_i)$ | Gaussian | 39.5 | $\hat{\rho} = 0.09$ [0.01, 0.18] |
| | Student-t | 0.5 | $\hat{\rho} = 0.06$ [0.06, 0.06]<br>$\hat{\upsilon} = 8.03$ [8.03, 8.03] |
| | Clayton | 5.3 | $\hat{\theta} = 0.33$ [0.08, 0.61] |
| | 90-Clayton | 8.4 | $\hat{\theta} = 0.27$ [0.04, 0.40] |
| | Gumbel | 13.2 | $\hat{\theta} = 1.16$ [1.13, 1.20] |
| | 90-Gumbel | 2.1 | $\hat{\theta} = 1.15$ [1.09,1.21] |
| | Independent | 31.1 | — |
| $C_{gb\|in}(u_g\|u_i, u_n; u_b\|u_i, u_n)$ | Gaussian | 0.5 | $\hat{\rho} = -0.02$ [−0.02, −0.02] |
| | Independent | 99.5 | — |

**Note.** This table presents a summary of the bivariate copula parameter estimates for the best copula fit between financial firms and the market as represented in the lower (shaded) panel in Figure 1. The third column indicates the percentage of financial firms for which bivariate dependence indicated in the first column is given by the copula function indicated in the second column. The last column reports average copula parameter estimates for the corresponding copula model, with numbers in the square brackets indicating the interquartile range.

**Table 6.** Summary statistics for climate transition systemic risk measures.

| | Climate transition scenarios | | |
|---|---|---|---|
| | Disorderly transition | Hot house world | Orderly transition |
| **Panel A.** Entire sample | | | |
| CTER | -0.0006 (0.0028) | -0.0138 (0.0134) | 0.0001 (0.0007) |
| CTVaR | -0.0341 (0.0111) | -0.0558 (0.0173) | -0.0407 (0.0129) |
| CTES | -0.0609 (0.0203) | -0.0881 (0.0267) | -0.0637 (0.0199) |
| **Panel B.** Banks | | | |
| CTER | -0.0081 (0.0030) | -0.0081 (0.0155) | -0.0012 (0.0006) |
| CTVaR | -0.0722 (0.0189) | -0.0485 (0.0144) | -0.0532 (0.0145) |
| CTES | -0.1003 (0.0268) | -0.0792 (0.0232) | -0.0806 (0.0216) |
| **Panel C.** Insurance companies | | | |
| CTER | 0.0013 (0.0019) | -0.0132 (0.0121) | 0.0013 (0.0010) |
| CTVaR | -0.0357 (0.0126) | -0.0555 (0.0188) | -0.0371 (0.0120) |
| CTES | -0.0609 (0.0210) | -0.0873 (0.0306) | -0.0589 (0.0192) |
| **Panel D.** Financial services | | | |
| CTER | 0.0053 (0.0039) | -0.0265 (0.0130) | 0.0012 (0.0016) |
| CTVaR | -0.0323 (0.0096) | -0.0664 (0.0169) | -0.0406 (0.0110) |
| CTES | -0.0596 (0.0176) | -0.1058 (0.0261) | -0.0645 (0.0173) |
| **Panel E.** Real state | | | |
| CTER | 0.0221 (0.0103) | -0.0232 (0.0111) | 0.0012 (0.0016) |
| CTVaR | -0.0225 (0.0089) | -0.0550 (0.0224) | -0.0366 (0.0138) |
| CTES | -0.0460 (0.0166) | -0.0851 (0.0334) | -0.0575 (0.0211) |

**Notes.** This table presents means values and standard deviation (in parenthesis) for the three climate transition systemic risk measures, CTER, CTVaR, and CTES, computed weekly over the sample period 2013-2020 for the entire sample and different categories of financial firms under three different climate transition scenarios.

**Table 7.** Average values of climate transition systemic risk impact for individual institutions.

| | Climate transition scenarios | | | | | | | | |
|---|---|---|---|---|---|---|---|---|---|
| | Disorderly transition | | | Hot house world | | | Orderly transition | | |
| | $CTER$ | $CTVaR$ | $CTES$ | $CTER$ | $CTVaR$ | $CTES$ | $CTER$ | $CTVaR$ | $CTES$ |
| **Panel A.** Banks | | | | | | | | | |
| HSBC | 0.0107 | -0.0173 | -0.0401 | -0.0739 | -0.1684 | -0.2053 | 0.0001 | -0.0288 | -0.0388 |
| BNP Paribas | 0.0161 | -0.0226 | -0.0538 | -0.0916 | -0.2099 | -0.2488 | 0.0023 | -0.0379 | -0.0519 |
| Santander | -0.018 | -0.0784 | -0.1106 | 0.0458 | -0.033 | -0.0637 | -0.0038 | -0.0589 | -0.0902 |
| Intesa Sanpaolo | -0.0013 | -0.0604 | -0.0914 | 0.0132 | -0.0604 | -0.0934 | -0.0029 | -0.0611 | -0.0918 |
| **Panel B.** Insurance | | | | | | | | | |
| Alliance | -0.0037 | -0.0404 | -0.0659 | -0.0157 | -0.0827 | -0.1516 | 0.0029 | -0.0338 | -0.0549 |
| Chubb | 0.0071 | -0.023 | -0.0408 | -0.0273 | -0.0819 | -0.1207 | 0.0032 | -0.0285 | -0.0436 |
| Zurich | 0.0001 | -0.0343 | -0.0571 | 0.0174 | -0.032 | -0.057 | 0.0000 | -0.0331 | -0.0552 |
| Axa | -0.0036 | -0.0468 | -0.072 | -0.0026 | -0.1122 | -0.1696 | 0.0001 | -0.0433 | -0.0645 |
| **Panel C.** Financial services | | | | | | | | | |
| UBS Group | -0.0059 | -0.0492 | -0.077 | -0.0204 | -0.0942 | -0.1612 | 0.0002 | -0.0437 | -0.0676 |
| London Stock | 0.0297 | -0.0111 | -0.0399 | -0.026 | -0.0802 | -0.1309 | 0.0033 | -0.0389 | -0.0673 |
| Deutsche Böerse | 0.0188 | -0.0168 | -0.0399 | -0.0161 | -0.0601 | -0.0899 | 0.002 | -0.0353 | -0.0566 |
| Credit Suisse | 0.012 | -0.0344 | -0.0669 | -0.087 | -0.1939 | -0.2429 | 0.0009 | -0.0502 | -0.0724 |
| **Panel D.** Real estate | | | | | | | | | |
| Deutsche Wohnen | 0.0205 | -0.0156 | -0.0389 | -0.0466 | -0.1197 | -0.1589 | 0.0043 | -0.0328 | -0.0508 |
| Segro | 0.0392 | -0.0119 | -0.0322 | -0.0119 | -0.0501 | -0.0696 | 0.0012 | -0.0341 | -0.051 |
| Gecina | 0.012 | -0.0235 | -0.0436 | -0.0109 | -0.05 | -0.0722 | 0.001 | -0.0343 | -0.0521 |
| LEG Immobilien | 0.0207 | -0.0128 | -0.0312 | -0.0154 | -0.0515 | -0.0721 | 0.0027 | -0.0299 | -0.0455 |

**Notes.** This table presents average values for three climate transition systemic risk measures, CTER, CTVaR, and CTES, computed weekly over the 2013-2020 period for the four largest individual firms within each category, considering three different climate transition scenarios.

**Table 8.** Factors influencing the CTER.

**Panel A.** Full sample

| | Climate transition scenarios | | | | | | | | | | | |
|---|---|---|---|---|---|---|---|---|---|---|---|---|
| | Disorderly transition | | | | Hot house world | | | | Orderly transition | | | |
| | (1) | (2) | (3) | (4) | (1) | (2) | (3) | (4) | (1) | (2) | (3) | (4) |
| Size | 0.085$^{*}$ | | | 0.066$^{**}$ | -0.213 | | | -0.117 | 0.013$^{**}$ | | | 0.007$^{**}$ |
| | (0.049) | | | (0.026) | (0.143) | | | (0.120) | (0.006) | | | (0.003) |
| Leverage | -0.003 | | | -0.002$^{*}$ | 0.004 | | | 0.002 | -0.000$^{***}$ | | | -0.000$^{***}$ |
| | (0.002) | | | (0.001) | (0.003) | | | (0.003) | (0.000) | | | (0.000) |
| ROA | -0.012 | | | -0.009 | 0.027$^{*}$ | | | 0.016$^{**}$ | -0.001$^{*}$ | | | -0.000$^{**}$ |
| | (0.008) | | | (0.006) | (0.014) | | | (0.006) | (0.000) | | | (0.000) |
| P/B | 0.049 | | | 0.054 | 0.186 | | | 0.156 | -0.006$^{**}$ | | | -0.004$^{*}$ |
| | (0.047) | | | (0.045) | (0.146) | | | (0.139) | (0.002) | | | (0.002) |
| $\beta$-CAPM | 0.084 | | | 0.051 | -0.358 | | | -0.275 | 0.007 | | | 0.006 |
| | (0.103) | | | (0.086) | (0.351) | | | (0.306) | (0.008) | | | (0.006) |
| Returns | | -0.405$^{**}$ | | -0.292$^{**}$ | | 1.620$^{**}$ | | 1.031 | | -0.095$^{***}$ | | -0.105$^{***}$ |
| | | (0.165) | | (0.145) | | (0.812) | | (0.627) | | (0.016) | | (0.015) |
| VIX | | 0.004 | | 0.005 | | -0.009 | | -0.015 | | -0.001 | | -0.001$^{***}$ |
| | | (0.004) | | (0.005) | | (0.018) | | (0.021) | | (0.000) | | (0.000) |
| Yield slope | | -0.079$^{***}$ | | -0.050$^{***}$ | | 0.281$^{***}$ | | 0.239$^{***}$ | | -0.010$^{***}$ | | -0.006$^{***}$ |
| | | (0.022) | | (0.019) | | (0.081) | | (0.072) | | (0.002) | | (0.002) |
| Default premium | | -0.129$^{***}$ | | -0.101$^{***}$ | | 0.507$^{***}$ | | 0.416$^{***}$ | | -0.012$^{***}$ | | -0.011$^{***}$ |
| | | (0.021) | | (0.030) | | (0.113) | | (0.123) | | (0.002) | | (0.002) |
| Ind. Prod. growth | | | -0.010$^{**}$ | -0.005 | | | 0.040$^{**}$ | 0.019$^{*}$ | | | -0.001$^{**}$ | -0.001$^{*}$ |
| | | | (0.005) | (0.004) | | | (0.018) | (0.011) | | | (0.001) | (0.000) |
| Inflation | | | 0.015 | 0.019 | | | -0.081 | -0.094$^{*}$ | | | 0.001 | -0.003$^{**}$ |
| | | | (0.018) | (0.018) | | | (0.067) | (0.056) | | | (0.003) | (0.001) |
| Unemployment gap | | | 0.034 | 0.016 | | | -0.074 | -0.015 | | | 0.002 | 0.000 |
| | | | (0.023) | (0.015) | | | (0.055) | (0.034) | | | (0.002) | (0.001) |
| R-squared | 0.04 | 0.05 | 0.03 | 0.09 | 0.06 | 0.11 | 0.04 | 0.15 | 0.03 | 0.06 | 0.01 | 0.08 |
| Observations | 1440 | 1440 | 1440 | 1440 | 1440 | 1440 | 1440 | 1440 | 1440 | 1440 | 1440 | 1440 |

**Panel B.** Banks

| | Climate transition scenarios | | | | | | | | | | | |
|---|---|---|---|---|---|---|---|---|---|---|---|---|
| | Disorderly transition | | | | Hot house world | | | | Orderly transition | | | |
| | (1) | (2) | (3) | (4) | (1) | (2) | (3) | (4) | (1) | (2) | (3) | (4) |
| Size | -0.090 | | | -0.004 | -0.258 | | | 0.214 | 0.033 | | | 0.014 |
| | (0.241) | | | (0.270) | (0.873) | | | (0.950) | (0.044) | | | (0.031) |
| Leverage | 0.001 | | | 0.001 | 0.016 | | | 0.011 | -0.003$^{***}$ | | | -0.002$^{***}$ |
| | (0.008) | | | (0.007) | (0.013) | | | (0.007) | (0.001) | | | (0.000) |
| ROA | 0.145$^{*}$ | | | 0.132$^{*}$ | -0.094 | | | -0.174 | -0.004 | | | 0.001 |
| | (0.084) | | | (0.075) | (0.119) | | | (0.155) | (0.004) | | | (0.002) |
| P/B | 0.162$^{*}$ | | | 0.147$^{***}$ | -0.043 | | | -0.154 | 0.015$^{**}$ | | | 0.020$^{***}$ |
| | (0.085) | | | (0.048) | (0.145) | | | (0.130) | (0.006) | | | (0.008) |
| $\beta$-CAPM | -0.144$^{*}$ | | | -0.161$^{***}$ | 0.069 | | | 0.104 | -0.003 | | | -0.007 |
| | (0.074) | | | (0.048) | (0.116) | | | (0.120) | (0.003) | | | (0.008) |
| Returns | | 0.267 | | 0.852$^{***}$ | | 0.290 | | -0.387 | | -0.076 | | -0.038 |
| | | (0.663) | | (0.259) | | (1.038) | | (0.606) | | (0.047) | | (0.034) |
| VIX | | -0.002 | | 0.023$^{***}$ | | -0.006 | | -0.036$^{*}$ | | -0.000 | | 0.001 |
| | | (0.014) | | (0.008) | | (0.018) | | (0.020) | | (0.001) | | (0.001) |
| Yield slope | | 0.141$^{*}$ | | 0.126$^{***}$ | | 0.041 | | 0.069 | | 0.003 | | 0.003 |
| | | (0.082) | | (0.044) | | (0.109) | | (0.067) | | (0.006) | | (0.004) |
| Default premium | | 0.042 | | -0.042 | | 0.178 | | 0.28 | | -0.023$^{***}$ | | -0.028$^{***}$ |
| | | (0.099) | | (0.043) | | (0.204) | | (0.175) | | (0.007) | | (0.006) |
| Ind. Prod. growth | | | -0.005 | -0.006 | | | 0.02 | 0.014 | | | -0.001$^{**}$ | -0.001 |
| | | | (0.006) | (0.004) | | | (0.015) | (0.015) | | | (0.001) | (0.001) |
| Inflation | | | 0.093$^{*}$ | 0.112$^{***}$ | | | -0.07 | -0.128$^{**}$ | | | 0.007$^{*}$ | 0.006$^{*}$ |
| | | | (0.049) | (0.032) | | | (0.046) | (0.054) | | | (0.004) | (0.003) |
| Unemployment gap | | | -0.003 | -0.028$^{**}$ | | | 0.018 | 0.048 | | | -0.0003 | -0.003 |
| | | | (0.010) | (0.013) | | | (0.045) | (0.063) | | | (0.001) | (0.002) |
| R-squared | 0.09 | 0.06 | 0.06 | 0.21 | 0.01 | 0.01 | 0.02 | 0.05 | 0.02 | 0.06 | 0.03 | 0.12 |
| Observations | 336 | 336 | 336 | 336 | 336 | 336 | 336 | 336 | 336 | 336 | 336 | 336 |

**Panel C.** Insurance firms

| | Climate transition scenarios | | | | | | | | | | | |
|---|---|---|---|---|---|---|---|---|---|---|---|---|
| | Disorderly transition | | | | Hot house world | | | | Orderly transition | | | |
| | (1) | (2) | (3) | (4) | (1) | (2) | (3) | (4) | (1) | (2) | (3) | (4) |
| Size | 0.076 | | | 0.109 | 0.075 | | | 0.074 | 0.018 | | | 0.015 |
| | (0.086) | | | (0.109) | (0.105) | | | (0.079) | (0.014) | | | (0.016) |
| Leverage | -0.008 | | | -0.009 | -0.024 | | | -0.026 | -0.001 | | | -0.001 |
| | (0.005) | | | (0.007) | (0.017) | | | (0.019) | (0.001) | | | (0.001) |
| ROA | -0.026 | | | -0.017 | 0.035 | | | 0.022 | -0.006 | | | -0.005 |
| | (0.030) | | | (0.029) | (0.031) | | | (0.034) | (0.004) | | | (0.005) |
| P/B | 0.159*** | | | 0.158*** | 0.016 | | | 0.033 | -0.007* | | | -0.008 |
| | (0.048) | | | (0.047) | (0.030) | | | (0.041) | (0.004) | | | (0.005) |
| $\beta$-CAPM | 0.037 | | | 0.011 | 0.042 | | | 0.202 | -0.003 | | | -0.007*** |
| | (0.064) | | | (0.047) | (0.138) | | | (0.159) | (0.003) | | | (0.001) |
| Returns | | -0.317 | | 0.274 | | 0.813 | | 0.528 | | -0.097*** | | -0.078** |
| | | (0.381) | | (0.299) | | (0.763) | | (0.583) | | (0.031) | | (0.039) |
| VIX | | -0.000 | | 0.015*** | | -0.013 | | -0.015 | | -0.001 | | -0.000 |
| | | (0.005) | | (0.006) | | (0.012) | | (0.013) | | (0.002) | | (0.001) |
| Yield slope | | -0.057 | | -0.047*** | | 0.101 | | 0.077 | | -0.005 | | -0.001 |
| | | (0.050) | | (0.015) | | (0.077) | | (0.049) | | (0.005) | | (0.005) |
| Default premium | | -0.148** | | -0.117** | | 0.394*** | | 0.362*** | | -0.009 | | -0.008 |
| | | (0.060) | | (0.046) | | (0.113) | | (0.110) | | (0.012) | | (0.005) |
| Ind. Prod. growth | | | -0.007 | 0.003 | | | 0.031* | 0.025*** | | | -0.000 | -0.000 |
| | | | (0.008) | (0.006) | | | (0.016) | (0.008) | | | (0.001) | (0.001) |
| Inflation | | | 0.085* | 0.098** | | | -0.096 | -0.086 | | | 0.003 | -0.002 |
| | | | (0.045) | (0.043) | | | (0.061) | (0.063) | | | (0.004) | (0.003) |
| Unemployment gap | | | 0.052* | 0.029 | | | -0.062 | -0.036 | | | 0.004 | 0.003 |
| | | | (0.031) | (0.024) | | | (0.041) | (0.042) | | | (0.003) | (0.004) |
| R-squared | 0.14 | 0.06 | 0.07 | 0.23 | 0.05 | 0.18 | 0.07 | 0.26 | 0.07 | 0.06 | 0.02 | 0.12 |
| Observations | 280 | 280 | 280 | 280 | 280 | 280 | 280 | 280 | 280 | 280 | 280 | 280 |

**Panel D.** Financial services

| | Climate transition scenarios | | | | | | | | | | | |
|---|---|---|---|---|---|---|---|---|---|---|---|---|
| | Disorderly transition | | | | Hot house world | | | | Orderly transition | | | |
| | (1) | (2) | (3) | (4) | (1) | (2) | (3) | (4) | (1) | (2) | (3) | (4) |
| Size | 0.027 | | | 0.018 | 0.044 | | | 0.103 | 0.0005 | | | -0.005 |
| | (0.019) | | | (0.014) | (0.117) | | | (0.147) | (0.005) | | | (0.005) |
| Leverage | -0.001$^{**}$ | | | -0.001$^{***}$ | 0.004 | | | 0.003 | -0.000$^{**}$ | | | -0.000 |
| | (0.001) | | | (0.000) | (0.004) | | | (0.004) | (0.000) | | | (0.000) |
| ROA | -0.002 | | | -0.000 | 0.019$^{**}$ | | | 0.009$^{**}$ | -0.000 | | | -0.000 |
| | (0.002) | | | (0.001) | (0.010) | | | (0.004) | (0.000) | | | (0.000) |
| P/B | -0.031 | | | -0.028 | 0.341 | | | 0.314 | -0.006$^{*}$ | | | -0.005$^{**}$ |
| | (0.033) | | | (0.030) | (0.293) | | | (0.262) | (0.003) | | | (0.003) |
| $\beta$-CAPM | 0.029 | | | 0.013 | -0.892 | | | -0.879 | 0.038 | | | 0.038$^{*}$ |
| | (0.084) | | | (0.077) | (0.854) | | | (0.767) | (0.025) | | | (0.021) |
| Returns | | -0.306$^{**}$ | | -0.116 | | 2.305$^{*}$ | | 0.539 | | -0.094$^{***}$ | | -0.105$^{***}$ |
| | | (0.132) | | (0.166) | | (1.306) | | (0.918) | | (0.024) | | (0.017) |
| VIX | | 0.003 | | 0.005 | | -0.012 | | -0.033 | | -0.0004 | | -0.001$^{***}$ |
| | | (0.003) | | (0.004) | | (0.024) | | (0.025) | | (0.001) | | (0.000) |
| Yield slope | | -0.076$^{***}$ | | -0.057$^{***}$ | | 0.368$^{**}$ | | 0.392$^{***}$ | | -0.017$^{***}$ | | -0.014$^{***}$ |
| | | (0.025) | | (0.017) | | (0.147) | | (0.115) | | (0.004) | | (0.004) |
| Default premium | | -0.092 | | -0.062$^{***}$ | | 0.711$^{***}$ | | 0.434$^{***}$ | | -0.010$^{***}$ | | -0.005$^{***}$ |
| | | (0.102) | | (0.019) | | (0.176) | | (0.138) | | (0.003) | | (0.002) |
| Ind. Prod. growth | | | -0.004 | 0.000 | | | 0.033 | 0.006 | | | -0.0004 | 0.000 |
| | | | (0.005) | (0.004) | | | (0.022) | (0.014) | | | (0.001) | (0.000) |
| Inflation | | | 0.007 | 0.015 | | | -0.148 | -0.224$^{*}$ | | | -0.002 | -0.004$^{*}$ |
| | | | (0.016) | (0.020) | | | (0.113) | (0.124) | | | (0.003) | (0.002) |
| Unemployment gap | | | 0.035$^{**}$ | 0.021 | | | -0.196$^{***}$ | -0.093$^{*}$ | | | 0.005$^{***}$ | 0.002$^{**}$ |
| | | | (0.014) | (0.014) | | | (0.072) | (0.053) | | | (0.002) | (0.001) |
| R-squared | 0.03 | 0.11 | 0.07 | 0.14 | 0.14 | 0.15 | 0.09 | 0.28 | 0.11 | 0.16 | 0.07 | 0.27 |
| Observations | 384 | 384 | 384 | 384 | 384 | 384 | 384 | 384 | 384 | 384 | 384 | 384 |

**Panel E.** Real estate firms

| | Climate transition scenarios | | | | | | | | | | | |
|---|---|---|---|---|---|---|---|---|---|---|---|---|
| | Disorderly transition | | | | Hot house world | | | | Orderly transition | | | |
| | (1) | (2) | (3) | (4) | (1) | (2) | (3) | (4) | (1) | (2) | (3) | (4) |
| Size | 0.295$^{*}$ | | | 0.143 | -0.785$^{**}$ | | | -0.341 | 0.028$^{***}$ | | | 0.008 |
| | (0.171) | | | (0.096) | (0.377) | | | (0.487) | (0.010) | | | (0.011) |
| Leverage | -0.019 | | | -0.016 | 0.038 | | | 0.081$^{**}$ | -0.001 | | | -0.003$^{*}$ |
| | (0.012) | | | (0.011) | (0.024) | | | (0.038) | (0.002) | | | (0.002) |
| ROA | -0.025$^{*}$ | | | -0.015$^{*}$ | 0.036$^{**}$ | | | 0.025$^{**}$ | -0.001 | | | -0.001$^{*}$ |
| | (0.014) | | | (0.008) | (0.017) | | | (0.010) | (0.001) | | | (0.000) |
| P/B | 0.117 | | | 0.120 | -0.200 | | | -0.363 | -0.018 | | | -0.013 |
| | (0.089) | | | (0.094) | (0.292) | | | (0.310) | (0.011) | | | (0.011) |
| $\beta$-CAPM | 0.463$^{*}$ | | | 0.308$^{*}$ | -1.053$^{**}$ | | | -0.785$^{*}$ | 0.005 | | | -0.001 |
| | (0.248) | | | (0.158) | (0.514) | | | (0.424) | (0.012) | | | (0.011) |
| Returns | | -1.034 | | -1.247$^{***}$ | | 2.524$^{**}$ | | 2.590$^{***}$ | | -0.108$^{**}$ | | -0.144$^{***}$ |
| | | (0.709) | | (0.304) | | (1.081) | | (0.870) | | (0.051) | | (0.050) |
| VIX | | 0.011 | | -0.000 | | -0.006 | | -0.001 | | -0.001 | | -0.002 |
| | | (0.018) | | (0.011) | | (0.031) | | (0.030) | | (0.001) | | (0.001) |
| Yield slope | | -0.257$^{***}$ | | -0.140$^{*}$ | | 0.496$^{***}$ | | 0.360 | | -0.018$^{***}$ | | -0.011$^{*}$ |
| | | (0.092) | | (0.082) | | (0.127) | | (0.315) | | (0.005) | | (0.007) |
| Default premium | | -0.273$^{**}$ | | -0.201$^{***}$ | | 0.646$^{***}$ | | 0.597$^{***}$ | | -0.008 | | -0.012$^{*}$ |
| | | (0.123) | | (0.059) | | (0.207) | | (0.201) | | (0.008) | | (0.007) |
| Ind. Prod. growth | | | -0.011 | 0.005 | | | 0.064$^{*}$ | 0.029 | | | -0.001$^{*}$ | -0.0004 |
| | | | (0.013) | (0.010) | | | (0.035) | (0.026) | | | (0.001) | (0.001) |
| Inflation | | | -0.076 | -0.098$^{***}$ | | | -0.009 | 0.030 | | | -0.002 | -0.010$^{***}$ |
| | | | (0.047) | (0.023) | | | (0.089) | (0.051) | | | (0.003) | (0.004) |
| Unemployment gap | | | 0.099$^{***}$ | 0.023 | | | -0.093$^{*}$ | 0.089 | | | 0.002 | -0.004$^{**}$ |
| | | | (0.023) | (0.029) | | | (0.048) | (0.082) | | | (0.002) | (0.002) |
| R-squared | 0.18 | 0.23 | 0.15 | 0.32 | 0.15 | 0.20 | 0.06 | 0.26 | 0.06 | 0.08 | 0.02 | 0.11 |
| Observations | 440 | 440 | 440 | 440 | 440 | 440 | 440 | 440 | 440 | 440 | 440 | 440 |

**Notes.** This table presents panel regression data for firm-specific, market, and macroeconomic determinants of CTER as given by Eq. (18). To control for unobserved heterogeneity, firm and temporal effects are included in all regressions. Standard errors (in brackets) were computed using double clustering at the firm and temporal levels. The asterisks $^{***}$, $^{**}$ and $^{*}$ indicate significance at the 1%, 5% and 10% level, respectively.

**Table 9.** Average capital shortfall effects of climate transition scenarios on individual firms.

| Climate transition scenarios | | | | | | | | |
|---|---|---|---|---|---|---|---|---|
| Disorderly transition | | | Hot house world | | | Orderly transition | | |
| | CTRISK | Market Cap. | | CTRISK | Market Cap. | | CTRISK | Market Cap. |
| **Panel A.** Banks | | | | | | | | |
| UniCredit S | 8249 | 27877 | Credit Agricole | 19274 | 29675 | Commerzbank | 1277 | 10399 |
| Commerzbank | 6072 | 10399 | HSBC | 13071 | 142005 | Natixis | 778 | 14932 |
| RBS | 3519 | 35177 | BNP Paribas | 7772 | 62636 | UniCredit S. | 745 | 27877 |
| Santander | 2289 | 70038 | Svenska H. AB | 525 | 21385 | Unione Banche I.. | 687 | 4053 |
| **Panel B.** Insurance | | | | | | | | |
| Swiss Life H. AG | 48 | 8773 | Aviva PLC | 421 | 19562 | CNP Assurances | 3 | 10818 |
| CNP Assurances | 45 | 10818 | Phoenix Group H. | 119 | 3593 | Beazley PLC | 1 | 2543 |
| Jardine Lloyd TG | 6 | 3375 | Legal General G. | 93 | 17019 | Zurich Insurance | 0 | 38941 |
| Beazley PLC | 0 | 2543 | Prudential PLC | 39 | 44925 | Willis Towers W. | 0 | 13929 |
| **Panel C.** Financial services | | | | | | | | |
| Deutsche Bank AG | 6141 | 26307 | Credit Suisse | 11477 | 31120 | Deutsche Bank AG | 334 | 26307 |
| Mediobanca | 332 | 6719 | UBS Group AG | 816 | 52165 | Mediobanca | 128 | 6719 |
| Grenke AG | 6 | 2565 | Mediobanca | 458 | 6719 | Aker ASA | 0 | 2558 |
| Axactor AB | 4 | 182 | Investec PLC | 445 | 5513 | Schroders PLC | 0 | 9149 |
| **Panel D.** Real estate | | | | | | | | |
| Intu Properties | 18 | 3452 | Fastighets Balder | 205 | 3473 | Fabege AB | 6 | 2796 |
| Fabege AB | 4 | 2796 | Swiss Prime | 155 | 5164 | Intu Properties | 4 | 3452 |
| CPI Property | 2 | 3904 | Immofinanz AG | 146 | 2538 | I. Colonial | 3 | 2784 |
| Grand City P. | 1 | 2464 | Klovern AB | 111 | 1383 | Grand City P. | 2 | 2464 |

**Notes.** This table presents average values (in millions of euros) for capital shortfall as given by the CTRISK for the four most impacted firms in each group under the three climate transition scenarios. Market Cap. denotes average market capitalization over the sample period 2013-2020.

## Appendix A

### Proof of Eq. (4)

We can express the joint probability $P\left(r_b \leq q_b^\alpha, r_g \geq q_g^\beta; r_n\right)$ from integration of the neutral asset as:

$$P\left(r_b \leq q_b^\alpha, r_g \geq q_g^\beta; r_n\right) = \int_{-\infty}^{+\infty} \left(P(r_b \leq q_b^\alpha | r_n) - P\left(r_b \leq q_b^\alpha, r_g \leq q_g^\beta | r_n\right)\right) f(r_n) dr_n,$$

where the conditional probabilities can be written using copulas as $P(r_b \leq q_b^\alpha | r_n) = C_{b|n}(\alpha | u_n)$ and $P\left(r_b \leq q_b^\alpha, r_g \leq q_g^\beta | r_n\right) = C_{bg|n}\left(C_{b|n}(\alpha | u_n), C_{g|n}(1-\beta | u_n)\right)$, where $P\left(r_g \leq q_g^\beta | r_n\right) = C_{g|n}(1-\beta | u_n)$ as $P\left(r_g \leq q_g^\beta\right) = 1-\beta$. Given that that $u_n = F_n(r_n)$, $du_n = f_n(r_n) dr_n$, it follows that the joint probability in term of copulas is:

$$P(r_b \leq q_b, r_g \geq q_g; r_n) = \int_0^1 \left\{C_{b|n}(\alpha | u_n) - C_{b,g|n}\left(C_{b|n}(\alpha | u_n), C_{g|n}(1-\beta | u_n)\right)\right\} du_n$$

### Proof of Eq. (5)

We compute $P\left(q_b^U \geq r_b \geq q_b^L, q_g^U \geq r_g \geq q_g^L, q_n^U \geq r_n \geq q_n^L\right)$ for a range of quantiles around the median, such that $P\left(q_b^U \geq r_b \geq q_b^L\right) = \alpha$, $P\left(q_g^U \geq r_g \geq q_g^L\right) = \beta$ and $P(q_n^U \geq r_n \geq q_n^L) = \delta$. Hence, $P\left(r_b \leq q_b^U\right) = 0.5 + \frac{\alpha}{2}$, $P\left(r_b \leq q_b^L\right) = 0.5 - \frac{\alpha}{2}$, $P\left(r_g \leq q_g^U\right) = 0.5 + \frac{\beta}{2}$, $P\left(r_g \leq q_g^L\right) = 0.5 - \frac{\beta}{2}$, $P(r_n \leq q_n^U) = 0.5 + \frac{\delta}{2}$, and $P(r_n \leq q_n^L) = 0.5 - \frac{\delta}{2}$.

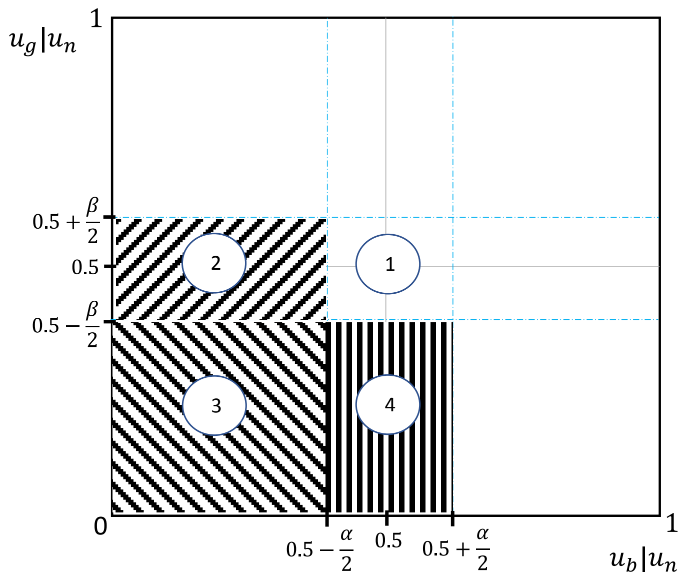
We can express the joint probability from integration of the neutral asset on the range of quantiles around its median as:

$$\begin{aligned} &P\left(q_b^U \geq r_b \geq q_b^L, q_g^U \geq r_g \geq q_g^L, q_n^U \geq r_n \geq q_n^L\right) \\ &\qquad = \int_{q_n^L}^{q_n^U} P\left(q_b^U \geq r_b \geq q_b^L, q_g^U \geq r_g \geq q_g^L | r_n\right) f(r_n) dr_n, \end{aligned}$$

where the joint conditional probability $P\left(q_b^U \geq r_b \geq q_b^L, q_g^U \geq r_g \geq q_g^L | r_n\right)$ can be decomposed as:

$$\begin{aligned} &P\left(q_b^U \geq r_b \geq q_b^L, q_g^U \geq r_g \geq q_g^L | r_n\right) \\ &\qquad = P\left(r_b \leq q_b^U, r_g \leq q_g^U | r_n\right) - P\left(r_b \leq q_b^L, r_g \leq q_g^L | r_n\right) \\ &\qquad - P\left(q_b^U \geq r_b \geq q_b^L, r_g \leq q_g^L | r_n\right) - P\left(r_b \leq q_b^L, q_g^U \geq r_g \geq q_g^L | r_n\right). \end{aligned}$$

The following figure represents the unit square for the joint distribution between conditional green and brown returns, illustrating the decomposition of the joint probability. The joint conditional probability we are looking for, $P\left(q_b^U \geq r_b \geq q_b^L, q_g^U \geq r_g \geq q_g^L | r_n\right)$, is given by box 1, with this box size decomposed as the total size of boxes 1, 2, 3, and 4 ($P\left(r_b \leq q_b^U, r_g \leq q_g^U | r_n\right)$) minus the size of boxes 2 ($P(r_b \leq q_b^L, q_g^U \geq r_g \geq\ q_g^L|r_n)$), 3 ($P(r_b \leq q_b^L, r_g \leq q_g^L|\ r_n)$), and 4 ($P(q_b^U \geq r_b \geq q_b^L, r_g \leq q_g^L|r_n)$).




Each of those four probabilities can be obtained from conditional copulas as:

a) $P(r_b \leq q_b^U, r_g \leq q_g^U|\ r_n) = C_{bg|n}\left(C_{b|n}\left(0.5+\frac{\alpha}{2}\middle|u_n\right), C_{g|n}\left(0.5+\frac{\beta}{2}\middle|u_n\right)\right)$

b) $P(r_b \leq q_b^L, r_g \leq q_g^L|\ r_n) = C_{bg|n}\left(C_{b|n}\left(0.5-\frac{\alpha}{2}\middle|u_n\right), C_{g|n}\left(0.5-\frac{\beta}{2}\middle|u_n\right)\right)$

c) $P(q_b^U \geq r_b \geq q_b^L, r_g \leq\ q_g^L|r_n) = C_{bg|n}\left(C_{b|n}\left(0.5+\frac{\alpha}{2}\middle|u_n\right), C_{g|n}\left(0.5-\frac{\beta}{2}\middle|u_n\right)\right) - C_{bg|n}\left(C_{b|n}\left(0.5-\frac{\alpha}{2}\middle|u_n\right), C_{g|n}\left(0.5-\frac{\beta}{2}\middle|u_n\right)\right)$

d) $P(r_b \leq q_b^L, q_g^U \geq r_g \geq\ q_g^L|r_n) = C_{bg|n}\left(C_{b|n}\left(0.5-\frac{\alpha}{2}\middle|u_n\right), C_{g|n}\left(0.5+\frac{\beta}{2}\middle|u_n\right)\right) - C_{bg|n}\left(C_{b|n}\left(0.5-\frac{\alpha}{2}\middle|u_n\right), C_{g|n}\left(0.5-\frac{\beta}{2}\middle|u_n\right)\right)$

Hence, the joint conditional probability can be obtained from copulas as:

$$\begin{aligned} P(q_b^U \geq r_b \geq q_b^L, q_g^U \geq r_g \geq\ q_g^L|r_n) &= C_{bg|n}\left(C_{b|n}(a|u_n), C_{g|n}(b|u_n)\right) + C_{bg|n}\left(C_{b|n}(d|u_n), C_{g|n}(e|u_n)\right) \\ &- C_{bg|n}\left(C_{b|n}(a|u_n), C_{g|n}(e|u_n)\right) - C_{bg|n}\left(C_{b|n}(d|u_n), C_{g|n}(b|u_n)\right), \end{aligned}$$

where $a = 0.5+\frac{\alpha}{2}$, $b = 0.5+\frac{\beta}{2}$, $d = 0.5-\frac{\alpha}{2}$ and $e = 0.5-\frac{\beta}{2}$.

Plugging the joint conditional probability into the integral and taking into account that $du_n = f_n(r_n)dr_n$, we can re-write the joint probability in term of copulas as:

$$P\left(q_b^U \geq r_b \geq q_b^L, q_g^U \geq r_g \geq q_g^L, q_n^U \geq r_n \geq q_n^L\right)$$

$$= \int_{0.5-\frac{\delta}{2}}^{0.5+\frac{\delta}{2}} \Big\{ C_{bg|n}\left(C_{b|n}(a|u_n), C_{g|n}(b|u_n)\right) + C_{bg|n}\left(C_{b|n}(d|u_n), C_{g|n}(e|u_n)\right) - C_{bg|n}\left(C_{b|n}(a|u_n), C_{g|n}(e|u_n)\right) - C_{bg|n}\left(C_{b|n}(d|u_n), C_{g|n}(b|u_n)\right)\Big\} du_n.$$

**Proof of Eq. (6)**

The joint density between financial firm *i* returns and the orderly transition scenario can be written as:

$$f\left(r_i, r_b \leq q_b^\alpha, r_g \geq q_g^\beta; r_n\right) = \int_{-\infty}^{\infty} f\left(r_i, r_b \leq q_b^\alpha, r_g \geq q_g^\beta | r_n\right) f_n(r_n) dr_n$$

$$= \int_{-\infty}^{\infty} f\left( r_b \leq q_b^\alpha, r_g \geq q_g^\beta | r_i, r_n\right) f(r_i|r_n) f_n(r_n) dr_n.$$

Note that, consistent with the dependence structure in Figure 1, $f(r_i|r_n) = f_i(r_i)$. Moreover, $f\left(r_b \leq q_b^\alpha, r_g \geq q_g^\beta | r_i, r_n\right) = P(r_b \leq q_b^\alpha | r_i, r_n) - P\left(r_b \leq q_b^\alpha, r_g \leq q_g^\beta \middle| r_i, r_n\right)$, where last two conditional probabilities can be written in terms of copulas as:

$P(r_b \leq q_b^\alpha | r_i, r_n) = C_{b|i,n}\left(C_{b|n}(\alpha|u_n)|u_i\right)$, and

$P\left(r_b \leq q_b^\alpha, r_g \leq q_g^\beta \middle| r_i, r_n\right) = C_{bg|i,n}\left(C_{b|i,n}\left(C_{b|n}(\alpha|u_n)\middle|u_i\right), C_{g|i,n}\left(C_{g|n}(1-\beta|u_n)\middle|u_i\right)\right)$.

Since $u_n = F_n(r_n)$, $du_n = f_n(r_n) dr_n$, the joint density can be expressed in terms of copulas as:

$$f\left(r_i, r_b \leq q_b^\alpha, r_g \geq q_g^\beta; r_n\right) =$$

$$= \int_0^1 \Big( C_{b|i,n}\left(C_{b|n}(\alpha|u_n)|u_i\right) - C_{bg|i,n}\left(C_{b|i,n}\left(C_{b|n}(\alpha|u_n)\middle|u_i\right), C_{g|i,n}\left(C_{g|n}(1-\beta|u_n)\middle|u_i\right)\right)\Big) f_i(F_i^{-1}(u_i)) du_n$$

**Proof of Eq. (7)**

We can express the joint density $f\left(r_i, q_b^U \geq r_b \geq q_b^L, q_g^U \geq r_g \geq q_g^L, q_n^U \geq r_n \geq q_n^L\right)$ as:

$$f\left(q_b^U \geq r_b \geq q_b^L, q_g^U \geq r_g \geq q_g^L, q_n^U \geq r_n \geq q_n^L | r_i\right) f_i(r_i),$$

where, in turn, the first density of this last expression can be decomposed as:

$$f\left(q_b^U \geq r_b \geq q_b^L, q_g^U \geq r_g \geq q_g^L, q_n^U \geq r_n \geq q_n^L | r_i\right)$$
$$= \int_{q_n^L}^{q_n^U} f\left(q_b^U \geq r_b \geq q_b^L, q_g^U \geq r_g \geq q_g^L | r_n, r_i\right) f_n(r_n) dr_n$$

Hence,

$$f\left(r_i, q_b^U \geq r_b \geq q_b^L, q_g^U \geq r_g \geq q_g^L, q_n^U \geq r_n \geq q_n^L\right)$$
$$= \int_{q_n^L}^{q_n^U} f\left(q_b^U \geq r_b \geq q_b^L, q_g^U \geq r_g \geq q_g^L | r_n, r_i\right) f_i(r_i) f_n(r_n) dr_n.$$

Since $f\left(q_b^U \geq r_b \geq q_b^L, q_g^U \geq r_g \geq q_g^L | r_n, r_i\right) = P(q_b^U \geq r_b \geq q_b^L, q_g^U \geq r_g \geq q_g^L | r_n, r_i)$, the joint conditional probability can be expressed in terms of copulas as:

$$P\left(q_b^U \geq r_b \geq q_b^L, q_g^U \geq r_g \geq q_g^L \middle| r_n, r_i\right)$$
$$= C_{bg|n,i}\left(C_{b|n,i}(a|\{u_n, u_i\}), C_{g|n,i}(b|\{u_n, u_i\})\right)$$
$$+ C_{bg|n,i}\left(C_{b|n,i}(d|\{u_n, u_i\}), C_{g|n,i}(e|\{u_n, u_i\})\right)$$
$$- C_{bg|n,i}\left(C_{b|n,i}(a|\{u_n, u_i\}), C_{g|n,i}(e|\{u_n, u_i\})\right)$$
$$- C_{bg|n,i}\left(C_{b|n,i}(d|\{u_n, u_i\}), C_{g|n,i}(b|\{u_n, u_i\})\right)$$

Using this last expression, and given that $u_n = F_n(r_n)$, $du_n = f_n(r_n) dr_n$, the joint density of the financial institution and the orderly transition scenario can be expressed as:

$$f\left(r_i, q_b^U \geq r_b \geq q_b^L, q_g^U \geq r_g \geq q_g^L, q_n^U \geq r_n \geq q_n^L\right)$$
$$= \int_{0.5-\frac{\delta}{2}}^{0.5+\frac{\delta}{2}} \Big\{ C_{bg|n,i}\left(C_{b|n,i}(a|\{u_n, u_i\}), C_{g|n,i}(b|\{u_n, u_i\})\right)$$
$$+ C_{bg|n,i}\left(C_{b|n,i}(d|\{u_n, u_i\}), C_{g|n,i}(e|\{u_n, u_i\})\right)$$
$$- C_{bg|n,i}\left(C_{b|n,i}(a|\{u_n, u_i\}), C_{g|n,i}(e|\{u_n, u_i\})\right)$$
$$- C_{bg|n,i}\left(C_{b|n,i}(d|\{u_n, u_i\}), C_{g|n,i}(b|\{u_n, u_i\})\right)\Big\} f_i\left(F_i^{-1}(u_i)\right) du_n$$

**Proof of Eq. (8)**

From Eq. (1), we have that

$$CTER_i = E\left(r_i \,\middle|\, r_g \geq q_g^{\beta}, r_b \leq q_b^{\alpha}; r_n\right) = \int_{-\infty}^{\infty} r_i \, \frac{f\left(r_i,\, r_g \geq q_g^{\beta}, r_b \leq q_b^{\alpha}; r_n\right)}{P\left(\, r_g \geq q_g^{\beta}, r_b \leq q_b^{\alpha}; r_n\right)} \, dr_i$$

$$= \frac{1}{P\left(\, r_g \geq q_g^{\beta}, r_b \leq q_b^{\alpha}; r_n\right)} \int_{-\infty}^{\infty} r_i \, \int_0^1 \left[ C_{b|i,n}\left(C_{b|n}(\alpha|u_n)|F_i(r_i)\right)\right.$$

$$\left. - C_{bg|i,n}\left(C_{b|i,n}\left(C_{b|n}(\alpha|u_n)\middle|F_i(r_i)\right), C_{g|i,n}\left(C_{g|n}(1-\beta|u_n)\middle|F_i(r_i)\right)\right)\right] f_i(r_i) du_n dr_i.$$

Since $u_i = F_i(r_i)$, $r_i = F_i^{-1}(u_i)$ and $du_i = f_i(r_i) dr_i$, we can write the previous expression as:

$$E\left(r_i \,\middle|\, r_g \geq q_g^{\beta}, r_b \leq q_b^{\alpha}; r_n\right)$$

$$= \frac{1}{\int_0^1 \left\{C_{b|n}(\alpha|u_n) - C_{b,g|n}\left(C_{b|n}(\alpha|u_n), C_{g|n}(1-\beta|u_n)\right)\right\} du_n} \int_0^1 F_i^{-1}(u_i) \int_0^1 \left\{C_{b|i,n}\left(C_{b|n}(\alpha|u_n)|u_i\right)\right.$$

$$\left. - C_{bg|i,n}\left(C_{b|i,n}\left(C_{b|n}(\alpha|u_n)\middle|u_i\right), C_{g|i,n}\left(C_{g|n}(1-\beta|u_n)\middle|u_i\right)\right)\right\} du_n du_i$$

**Proof of Eq. (9)**

For an orderly climate transition scenario we have that

$$CTER_i = E\left(r_i \,\middle|\, q_b^L \leq r_b \leq q_b^U, q_g^L \leq r_g \leq q_g^U, q_n^L \leq r_n \leq q_n^U\right) =$$

$$= \frac{1}{P\left(q_b^U \geq r_b \geq q_b^L, q_g^U \geq r_g \geq \; q_g^L, q_n^U \geq r_n \geq q_n^L\right)} \int_{-\infty}^{\infty} r_i \, f\left(r_i, q_b^U \geq r_b \geq q_b^L, q_g^U\right.$$

$$\left. \geq r_g \geq \; q_g^L, q_n^U \geq r_n \geq q_n^L\right) dr_i$$

where $P\left(q_b^U \geq r_b \geq q_b^L, q_g^U \geq r_g \geq \; q_g^L, q_n^U \geq r_n \geq q_n^L\right)$ is given by Eq. (5). Plugging the value of the joint density $f\left(r_i, q_b^U \geq r_b \geq q_b^L, q_g^U \geq r_g \geq \; q_g^L, q_n^U \geq r_n \geq q_n^L\right)$ as given by Eq. (7) into $CTER_i$, and taking into account that $u_n = F_n(r_n)$, $du_n = f_n(r_n) dr_n$ and $u_i = F_i(r_i)$, $du_i = f_i(r_i) dr_i$, the expected shortfall for an orderly transition can be expressed in terms of copulas as:

$$E\left(r_i \middle| q_b^U \geq r_b \geq q_b^L, q_g^U \geq r_g \geq \; q_g^L, q_n^U \geq r_n \geq q_n^L\right)$$

$$= \frac{1}{P\left(q_b^U \geq r_b \geq q_b^L, q_g^U \geq r_g \geq \; q_g^L, q_n^U \geq r_n \geq q_n^L\right)} \int_0^1 \int_{0.5-\frac{\delta}{2}}^{0.5+\frac{\delta}{2}} F_i^{-1}(u_i)$$

$$\Big\{C_{bg|n,i}\left(C_{b|n,i}(a|\{u_n,u_i\}),C_{g|n,i}(b|\{u_n,u_i\})\right)$$
$$+C_{bg|n,i}\left(C_{b|n,i}(d|\{u_n,u_i\}),C_{g|n,i}(e|\{u_n,u_i\})\right)$$
$$-C_{bg|n,i}\left(C_{b|n,i}(a|\{u_n,u_i\}),C_{g|n,i}(e|\{u_n,u_i\})\right)$$
$$-C_{bg|n,i}\left(C_{b|n,i}(d|\{u_n,u_i\}),C_{g|n,i}(b|\{u_n,u_i\})\right)\Big\}du_n du_i.$$

**Proof of Eq. (10)**

The joint probability $P\left(r_b \leq q_b^{\alpha}, r_g \geq q_g^{\beta}, r_i \leq CTVaR_i^{\gamma}; r_n\right)$ is given by the difference between $P\left(r_b \leq q_b^{\alpha}, r_i \leq CTVaR_i^{\gamma}; r_n\right)$ and $P\left(r_b \leq q_b^{\alpha}, r_g \leq q_g^{\beta}, r_i \leq CTVaR_i^{\gamma}; r_n\right)$. The first probability is defined as:

$$\begin{aligned}
P\left(r_b \leq q_b^{\alpha}, r_i \leq CTVaR_i^{\gamma}; r_n\right) &= \int_{-\infty}^{\infty} P\left(r_b \leq q_b^{\alpha}, r_i \leq CTVaR_i^{\gamma} | r_n\right) f_n(r_n) dr_n \\
&= \int_0^1 C_{bi|n}\left(C_{b|n}(\alpha|u_n), F_i\left(CTVaR_i^{\gamma}\right)\right) du_n \\
&= \int_0^{F_i\left(CTVaR_i^{\gamma}\right)} \int_0^1 C_{b|i,n}\left(C_{b|n}(\alpha|u_n)|u_i\right) du_n du_i,
\end{aligned}$$

where, in the second equality, $F_i\left(CTVaR_i^{\gamma}\right) = P\left(r_i \leq CTVaR_i^{\gamma}\right)$. Note that $F_i\left(CTVaR_i^{\gamma}\right)$ is different from $\gamma$ as the unconditional distribution of *i* differs from the distribution of *i* conditional on a climate transition scenario ($CTVaR_i^{\gamma}$ is a quantile of that conditional distribution). The second probability can be obtained as:

$$\begin{aligned}
&P\left(r_b \leq q_b^{\alpha}, r_g \leq q_g^{\beta}, r_i \leq CTVaR_i^{\gamma}; r_n\right) \\
&= \int_{-\infty}^{CTVaR_i^{\gamma}} \int_{-\infty}^{\infty} P\left(r_b \leq q_b^{\alpha}, r_g \leq q_g^{\beta} \middle| r_n, r_i\right) f(r_i\,|r_n) f_n(r_n) dr_n dr_i \\
&= \int_0^{F_i\left(CTVaR_i^{\gamma}\right)} \int_0^1 C_{bg|i,n}\left(C_{b|i,n}\left(C_{b|n}(\alpha|u_n)\middle|u_i\right), C_{g|i,n}\left(C_{g|n}(1-\beta|u_n)\middle|u_i\right)\right) du_n du_i,
\end{aligned}$$

where $f(r_i\,|r_n) = f_i(r_i\,)$. From the copula representation of those two probabilities, we therefore have:

$$\begin{aligned}
&P\left(r_b \leq q_b, r_g \geq q_g, r_i \leq CTVaR_i^{\gamma}; r_n\right) \\
&\qquad = \int_0^{F_i\left(CTVaR_i^{\gamma}\right)} \int_0^1 \Big\{C_{b|i,n}\left(C_{b|n}(\alpha|u_n)\middle|u_i\right) \\
&\qquad - C_{bg|i,n}\left(C_{b|i,n}\left(C_{b|n}(\alpha|u_n)\middle|u_i\right), C_{g|i,n}\left(C_{g|n}(1-\beta|u_n)\middle|u_i\right)\right)\Big\} du_n du_i
\end{aligned}$$

**Proof of Eq. (11)**

$P\left(r_i \le CTVaR_i^\gamma \middle| r_g \ge q_g^\beta, r_b \le q_b^\alpha; r_n\right)$ is given by copulas as the ratio between $P\left(r_i \le CTVaR_i^\gamma, r_g \ge q_g^\beta, r_b \le q_b^\alpha; r_n\right)$ and the conditioning probability $P\left(r_g \ge q_g^\beta, r_b \le q_b^\alpha; r_n\right)$, which can be expressed in terms of copulas as shown in the proofs of Eqs. (4) and (10). Thus, $P\left(r_i \le CTVaR_i^\gamma \middle| r_g \ge q_g^\beta, r_b \le q_b^\alpha; r_n\right)$ can be written as:

$$\frac{\int_0^{F_i(CTVaR_i^\gamma)} \int_0^1 \left\{C_{b|i,n}\left(C_{b|n}(\alpha|u_n)\middle|u_i\right) - C_{b,g|i,n}\left(C_{b|i,n}\left(C_{b|n}(\alpha|u_n)\middle|u_i\right), C_{g|i,n}\left(C_{g|n}(1-\beta|u_n)\middle|u_i\right)\right)\right\} du_n du_i}{\int_0^1 \left\{C_{b|n}(\alpha|u_n) - C_{b,g|n}\left(C_{b|n}(\alpha|u_n), C_{g|n}(1-\beta|u_n)\right)\right\} du_n}$$

The value of this ratio is a function of $F_i(CTVaR_i^\gamma)$. We denote the ratio as a function $G\left(F_i(CTVaR_i^\gamma)\right)$. Since $G\left(F_i(CTVaR_i^\gamma)\right) = \gamma$, then $F_i(CTVaR_i^\gamma) = G^{-1}(\gamma)$. Hence, $CTVaR_i^\gamma = F_i^{-1}(G^{-1}(\gamma))$.

**Proof of Eq. (12)**

Using the joint density $f\left(r_i, q_b^U \ge r_b \ge q_b^L, q_g^U \ge r_g \ge q_g^L, q_n^U \ge r_n \ge q_n^L\right)$ in Eq. (7), we can obtain the joint probability $P\left(r_i \le CTVaR_i^\gamma, q_b^U \ge r_b \ge q_b^L, q_g^U \ge r_g \ge q_g^L, q_n^U \ge r_n \ge q_n^L\right)$ as:

$$P\left(r_i \le CTVaR_i^\gamma, q_b^U \ge r_b \ge q_b^L, q_g^U \ge r_g \ge q_g^L, q_n^U \ge r_n \ge q_n^L\right)$$

$$= \int_{-\infty}^{CTVaR_i^\gamma} f\left(r_i, q_b^U \ge r_b \ge q_b^L, q_g^U \ge r_g \ge q_g^L, q_n^U \ge r_n \ge q_n^L\right) dr_i,$$

In terms of copulas, this is:

$$P\left(r_i \le CTVaR_i^\gamma, q_b^U \ge r_b \ge q_b^L, q_g^U \ge r_g \ge q_g^L, q_n^U \ge r_n \ge q_n^L\right)$$

$$\begin{aligned}
&= \int_0^{F_i(CTVaR_i^\gamma)} \left\{ \int_{0.5-\frac{\delta}{2}}^{0.5+\frac{\delta}{2}} \left\{ C_{bg|n,i}\left(C_{b|n,i}(a|\{u_n,u_i\}), C_{g|n,i}(b|\{u_n,u_i\})\right) \right.\right. \\
&+ C_{bg|n,i}\left(C_{b|n,i}(d|\{u_n,u_i\}), C_{g|n,i}(e|\{u_n,u_i\})\right) \\
&- C_{bg|n,i}\left(C_{b|n,i}(a|\{u_n,u_i\}), C_{g|n,i}(e|\{u_n,u_i\})\right) \\
&\left.\left. - C_{bg|n,i}\left(C_{b|n,i}(d|\{u_n,u_i\}), C_{g|n,i}(b|\{u_n,u_i\})\right)\right\} du_n \right\} du_i.
\end{aligned}$$

**Proof of Eq. (13)**

From Eq. (3), the $CTES_i^\gamma$ is given by:

$$E\left(r_i \middle| r_g \geq q_g^\beta, r_b \leq q_b^\alpha, r_i \leq CTVaR_i^\gamma; r_n\right) =$$

$$= \frac{1}{P\left(r_g \geq q_g^\beta, r_b \leq q_b^\alpha, r_i \leq CTVaR_i^\gamma; r_n\right)} \int_{-\infty}^{CTVaR_i^\gamma} r_i\, f\left(r_i, r_g \geq q_g^\beta, r_b \leq q_b^\alpha; r_n\right)\, dr_i.$$

We can rewrite the joint density in the previous expression as:

$$\begin{aligned} f\left(r_i, r_g \geq q_g^\beta, r_b \leq q_b^\alpha; r_n\right) &= \int_{-\infty}^{\infty} f\left(r_i, r_b \leq q_b^\alpha, r_g \geq q_g^\beta | r_n\right) f_n(r_n) dr_n \\ &= \int_{-\infty}^{\infty} f\left(r_b \leq q_b^\alpha, r_g \geq q_g^\beta | r_i, r_n\right) f(r_i|r_n) f_n(r_n) dr_n \end{aligned}$$

where $f(r_i|r_n) = f_i(r_i)$ and $f\left(r_b \leq q_b, r_g \geq q_g | r_i, r_n\right) = P(r_b \leq q_b^\alpha | r_i, r_n) -$ $P\left(r_b \leq q_b^\alpha, r_g \leq q_g^\beta \middle| r_i, r_n\right)$. Those last two conditional probabilities can be written in terms of copulas as:

$$P(r_b \leq q_b^\alpha | r_i, r_n) = C_{b|i,n}\left(C_{b|n}(\alpha|u_n)|u_i\right),$$

$$P\left(r_b \leq q_b^\alpha, r_g \leq q_g^\beta \middle| r_i, r_n\right) = C_{bg|i,n}\left(C_{b|i,n}\left(C_{b|n}(\alpha|u_n)\middle|u_i\right), C_{g|i,n}\left(C_{g|n}(1-\beta|u_n)\middle|u_i\right)\right).$$

Now, plugging those results into $\int_{-\infty}^{\infty} r_i\, f\left(r_i, r_g \geq q_g^\beta, r_b \leq q_b^\alpha, r_i; r_n\right) dr_i$, and taking into account that $u_i = F_i(r_i)$, $du_i = f_i(r_i) dr_i$, we can write

$$\begin{aligned} &\int_{-\infty}^{CTVaR_i^\gamma} r_i\, f\left(r_i, r_g \geq q_g^\beta, r_b \leq q_b^\alpha, r_i; r_n\right) dr_i \\ &\qquad = \int_0^{F_i\left(CTVaR_i^\gamma\right)} \int_0^1 F_i^{-1}(u_i) \Big\{ C_{b|i,n}\left(C_{b|n}(\alpha|u_n)\middle|u_i\right) \\ &\qquad - C_{bg|i,n}\left(C_{b|i,n}\left(C_{b|n}(\alpha|u_n)\middle|u_i\right), C_{g|i,n}\left(C_{g|n}(1-\beta|u_n)\middle|u_i\right)\right) \Big\} du_n du_i \end{aligned}$$

**Proof of Eq. (14)**

The joint probability $P\left(r_g \geq q_g^\beta, r_b \leq q_b^\alpha, r_i \leq CTVaR_i^\gamma; r_n\right)$ is given by the difference between $P\left(r_b \leq q_b^\alpha, r_i \leq CTVaR_i^\gamma; r_n\right)$ and $P\left(r_b \leq q_b^\alpha, r_g \leq q_g^\beta, r_i \leq CTVaR_i^\gamma; r_n\right)$, where:

$P\left(r_b \leq q_b^\alpha, r_i \leq CTVaR_i^\gamma; r_n\right) = \sum_{k=-\infty}^{\infty} P\left(r_b \leq q_b^\alpha, r_i \leq CTVaR_i^\gamma | r_n = k\right) P(r_n = k)$, and

$P\left(r_b \leq q_b^{\alpha}, r_g \leq q_g^{\beta}, r_i \leq CTVaR_i^{\gamma}\right) = \sum_{j=-\infty}^{CTVaR_i^{\gamma}} \sum_{k=-\infty}^{\infty} P(r_b \leq q_b^{\alpha}, r_g \leq q_g^{\beta} | r_n = k, r_i = j\ )\ P(r_n = k) P(r_i = j\ )$. Using copulas, we have:

$$
\begin{aligned}
&P\left(r_g \geq q_g^{\beta}, r_b \leq q_b^{\alpha}, r_i \leq CTVaR_i^{\gamma}; r_n\right) \\
&\qquad = \int_0^{F_i\left(CTVaR_i^{\gamma}\right)} \int_0^1 \Big\{ C_{b|i,n}\big(C_{b|n}(\alpha|u_n)\big|u_i\big) \\
&\qquad - C_{b,g|i,n}\left(C_{b|i,n}\big(C_{b|n}(\alpha|u_n)\big|u_i\big), C_{g|i,n}\big(C_{g|n}(1-\beta|u_n)\big|u_i\big)\right)\Big\} du_n du_i
\end{aligned}
$$

**Proof of Eq. (15)**

Using Eq. (7), we can express the joint density $f\left(r_i \leq CTVaR_i^{\gamma}, q_b^U \geq r_b \geq q_b^L, q_g^U \geq r_g \geq q_g^L, q_n^U \geq r_n \geq q_n^L\right)$ as:

$$
\begin{aligned}
&f\left(r_i \leq CTVaR_i^{\gamma}, q_b^U \geq r_b \geq q_b^L, q_g^U \geq r_g \geq q_g^L, q_n^U \geq r_n \geq q_n^L\right) \\
&\qquad = \int_0^{F_i\left(CTVaR_i^{\gamma}\right)} \left\{ \int_{0.5-\frac{\delta}{2}}^{0.5+\frac{\delta}{2}} \Big\{ C_{bg|n,i}\left(C_{b|n,i}(a|\{u_n,u_i\}), C_{g|n,i}(b|\{u_n,u_i\})\right) \right. \\
&\qquad + C_{bg|n,i}\left(C_{b|n,i}(d|\{u_n,u_i\}), C_{g|n,i}(e|\{u_n,u_i\})\right) \\
&\qquad - C_{bg|n,i}\left(C_{b|n,i}(a|\{u_n,u_i\}), C_{g|n,i}(e|\{u_n,u_i\})\right) \\
&\qquad \left. - C_{bg|n,i}\left(C_{b|n,i}(d|\{u_n,u_i\}), C_{g|n,i}(b|\{u_n,u_i\})\right)\Big\} f_i(r_i) du_n \right\} du_i \\
&\qquad = \int_0^{F_i\left(CTVaR_i^{\gamma}\right)} f\left(r_i, q_b^U \geq r_b \geq q_b^L, q_g^U \geq r_g \geq q_g^L, q_n^U \geq r_n \geq q_n^L\right) du_i
\end{aligned}
$$

## Appendix B

Below we describe how to sample from the C-vine characterizing dependence between market assets. Using the algorithm in Aas et al. (2009), we draw a sample *s* from the C-vine structure to obtain $u_{g,T+h}^{(s)}$, $u_{n,T+h}^{(s)}$ and $u_{b,T+h}^{(s)}$.

We first sample three independent uniform variables on [0,1]: $\omega_1$, $\omega_2$ and $\omega_3$. Next:

(a) we set $u_{n,T+h}^{(s)} = \omega_1$;

(b) given that $C_{g|n}\left(u_{g,T+h}^{(s)} \middle| u_{n,T+h}^{(s)}; \theta_{gn,T+h}\right) = \omega_2$, therefore $u_{g,T+h}^{(s)}$ can be obtained as $u_{g,T+h}^{(s)} = C_{g|n}^{-1}\left(\omega_2 \middle| u_{n,T+h}^{(s)}; \theta_{gn,T+h}\right)$;

(c) since $C_{b|gn}\left(C_{b|n}(u_{b,T+h}^{(s)}|u_{n,T+h}^{(s)}; \theta_{bn,T+h}) \middle| C_{g|n}(u_{g,T+h}^{(s)}|u_{n,T+h}^{(s)}; \theta_{gn,T+h}); \theta_{gb|n,T+h}\right) = \omega_3$, we have $C_{b|n}\left(u_{b,T+h}^{(s)} \middle| u_{n,T+h}^{(s)}; \theta_{bn,T+h}\right) = C_{b|gn}^{-1}\left(\omega_3 | C_{g|n}(u_{g,T+h}^{(s)}|u_{n,T+h}^{(s)}; \theta_{gn,T+h}); \theta_{gb|n,T+h}\right)$, and thus $u_{b,T+h}^{(s)} = C_{b|n}^{-1}\left(C_{b|n}(u_{b,T+h}^{(s)}|u_{n,T+h}^{(s)}; \theta_{bn,T+h}) \middle| u_{n,T+h}^{(s)}; \theta_{bn,T+h}\right)$.

## Appendix C

Below we report information on the conditional copula density of financial institution *i in* the market, $C\left(v|u_{g,T+h}^{(s)}, u_{n,T+h}^{(s)}, u_{b,T+h}^{(s)}\right)$.

This conditional copula can be seen as a ratio of two probabilities, i.e.,

$$C\left(v|u_{g,T+h}^{(s)}, u_{n,T+h}^{(s)}, u_{b,T+h}^{(s)}\right) = \frac{\int_0^v c\left(u_i, u_{g,T+h}^{(s)}, u_{n,T+h}^{(s)}, u_{b,T+h}^{(s)}\right) du_i}{\int_0^1 c\left(u_i, u_{g,T+h}^{(s)}, u_{n,T+h}^{(s)}, u_{b,T+h}^{(s)}\right) du_i},$$

where c(…) indicates the copula density. According to the dependence structure presented in Figure 1 we define $c\left(u_i, u_{g,T+h}^{(s)}, u_{n,T+h}^{(s)}, u_{b,T+h}^{(s)}\right)$ as:

$$c_{gn}\left(u_{g,T+h}^{(s)}, u_{n,T+h}^{(s)}; \theta_{gn,T+h}\right) c_{gi|n}\left(C_{g|n}\left(u_{g,T+h}^{(s)}\middle|u_{n,T+h}^{(s)}\right), u_i; \theta_{gi|n;T+h}\right)$$

$$c_{bn}\left(u_{b,T+h}^{(s)}, u_{n,T+h}^{(s)}; \theta_{bn,T+h}\right) c_{bi|n}\left(C_{b|n}\left(u_{b,T+h}^{(s)}\middle|u_{n,T+h}^{(s)}\right), u_i; \theta_{bi|n;T+h}\right)$$

$$c_{gb|i,n}\left(C_{g|i,n}\left(u_{g,T+h}^{(s)}\middle|u_i, u_{n,T+h}^{(s)}; \theta_{gi|n;T+h}\right), C_{b|i,n}\left(u_{b,T+h}^{(s)}\middle|u_i, u_{n,T+h}^{(s)}; \theta_{bi|n;T+h}\right); \theta_{gb|i,n;T+h}\right)$$

where $\theta_{gi|n;\,T+h}$, $\theta_{bi|n,;T+h}$ and $\theta_{gb|i,n;\,T+h}$ denote the respective copula parameters that are updated using information up to *T+h-1* according to the dynamics indicated in Table 1, or alternatively, remain stable if the best fit copula is static. Thus, by plugging the copula density into the conditional copula density, then simplifying by cancelling the parts of the copula density in the numerator and denominator that are not affected by the integration, we have:

$$C\left(v|u_{g,T+h}^{(s)}, u_{n,T+h}^{(s)}, u_{b,T+h}^{(s)}\right) = \frac{\int_0^v g\left(u_i, u_{g,T+h}^{(s)}, u_{n,T+h}^{(s)}, u_{b,T+h}^{(s)}\right) du_i}{\int_0^1 g(u_i, u_{g,T+h}^{(s)}, u_{n,T+h}^{(s)}, u_{b,T+h}^{(s)})\, du_i},$$

where

$$g(u_i, u_{g,T+h}^{(s)}, u_{n,T+h}^{(s)}, u_{b,T+h}^{(s)})$$
$$= c_{gb|i,n}\left(C_{g|i,n}\left(u_{g,T+h}^{(s)}\middle|u_i, u_{n,T+h}^{(s)}; \theta_{gi|n;T+h}\right), C_{b|i,n}\left(u_{b,T+h}^{(s)}\middle|u_i, u_{n,T+h}^{(s)}; \theta_{bi|n;t+h}\right); \theta_{gb|i,n;t+h}\right)$$
$$c_{gi|n}\left(C_{g|n}\left(u_{g,T+h}^{(s)}\middle|u_{n,T+h}^{(s)}\right), u_i; \theta_{gi|n;t+h}\right) c_{bi|n}\left(C_{b|n}\left(u_{b,T+h}^{(s)}\middle|u_{n,T+h}^{(s)}\right), u_i; \theta_{bi|n;t+h}\right).$$

# Online appendix

**Table A1.** List of financial firms in the sample.

| Firm name | Country | Industry group |
|---|---|---|
| Erste Group Bank AG | Austria | Banks |
| Raiffeisen Bank International AG | Austria | Banks |
| KBC Group NV | Belgium | Banks |
| Danske Bank A/S | Denmark | Banks |
| Jyske Bank A/S | Denmark | Banks |
| Sydbank A/S | Denmark | Banks |
| Credit Agricole S.A. | France | Banks |
| BNP Paribas SA | France | Banks |
| Societe Generale SA | France | Banks |
| Natixis S.A. | France | Banks |
| Aareal Bank AG | Germany | Banks |
| Commerzbank AG | Germany | Banks |
| AIB Group PLC | Ireland | Banks |
| Bank of Ireland Group PLC | Ireland | Banks |
| BANCO BPM – Società per azioni | Italy | Banks |
| Intesa Sanpaolo S.p.A. | Italy | Banks |
| Unione di Banche Italiane S.p.A. | Italy | Banks |
| UniCredit S.p.A. | Italy | Banks |
| ING Groep N.V. | Netherlands | Banks |
| DNB ASA | Norway | Banks |
| SpareBank 1 SMN | Norway | Banks |
| SpareBank 1 SR-Bank ASA | Norway | Banks |
| mBank S.A. | Poland | Banks |
| Bank Pekao S.A. | Poland | Banks |
| PKO Bank Polski SA | Poland | Banks |
| Santander Bank Polska SA | Poland | Banks |
| Banco Comercial Portugues S.A. | Portugal | Banks |
| Banco Bilbao Vizcaya Argentaria SA | Spain | Banks |
| Bankia SA | Spain | Banks |
| Bankinter, S.A. | Spain | Banks |
| CaixaBank, S.A. | Spain | Banks |
| Banco de Sabadell, S.A. | Spain | Banks |
| Banco Santander, S.A. | Spain | Banks |
| Nordea Bank AB | Sweden | Banks |
| Skandinaviska Enskilda Banken AB | Sweden | Banks |
| Svenska Handelsbanken AB | Sweden | Banks |
| Swedbank AB | Sweden | Banks |
| Barclays PLC | United Kingdom | Banks |
| HSBC Holdings PLC | United Kingdom | Banks |

**Table A1 (Cont.).** List of financial firms in the sample.

| Firm name | Country | Industry group |
|---|---|---|
| Lloyds Banking Group PLC | United Kingdom | Banks |
| Paragon Banking Group PLC | United Kingdom | Banks |
| The Royal Bank of Scotland Group plc | United Kingdom | Banks |
| Standard Chartered PLC | United Kingdom | Banks |
| UNIQA Insurance Group AG | Austria | Insurance |
| Vienna Insurance Group AG | Austria | Insurance |
| Ageas SA/NV | Belgium | Insurance |
| Tryg A/S | Denmark | Insurance |
| Sampo Oyj | Finland | Insurance |
| CNP Assurances SA | France | Insurance |
| AXA SA | France | Insurance |
| SCOR SE | France | Insurance |
| Allianz SE | Germany | Insurance |
| Hannover Rueck SE | Germany | Insurance |
| Muenchener Rueckversicherungs-Gesellschaft AG | Germany | Insurance |
| Talanx AG | Germany | Insurance |
| Assicurazioni Generali S.p.A. | Italy | Insurance |
| Aegon NV | Netherlands | Insurance |
| Gjensidige Forsikring ASA | Norway | Insurance |
| Storebrand ASA | Norway | Insurance |
| Powszechny Zaklad Ubezpieczen SA | Poland | Insurance |
| Mapfre, S.A. | Spain | Insurance |
| Baloise Holding AG | Switzerland | Insurance |
| Chubb Ltd | Switzerland | Insurance |
| Helvetia Holding AG | Switzerland | Insurance |
| Swiss Life Holding AG | Switzerland | Insurance |
| Swiss Re Ltd. | Switzerland | Insurance |
| Zurich Insurance Group AG | Switzerland | Insurance |
| Admiral Group PLC | United Kingdom | Insurance |
| Aviva PLC | United Kingdom | Insurance |
| Beazley PLC | United Kingdom | Insurance |
| Direct Line Insurance Group PLC | United Kingdom | Insurance |
| Jardine Lloyd Thompson Group PLC | United Kingdom | Insurance |
| Legal & General Group PLC | United Kingdom | Insurance |
| Lancashire Holdings Ltd | United Kingdom | Insurance |
| Phoenix Group Holdings | United Kingdom | Insurance |
| Prudential PLC | United Kingdom | Insurance |
| RSA Insurance Group PLC | United Kingdom | Insurance |
| Standard Life Aberdeen PLC | United Kingdom | Insurance |

**Table A1 (Cont.).** List of financial firms in the sample.

| Firm name | Country | Industry group |
|---|---|---|
| Willis Towers Watson Public Limited Company | United Kingdom | Insurance |
| CA Immobilien Anlagen Aktiengesellschaft | Austria | Real Estate |
| Immofinanz AG | Austria | Real Estate |
| S IMMO AG | Austria | Real Estate |
| Cofinimmo S.A. | Belgium | Real Estate |
| Warehouses De Pauw Comm. VA | Belgium | Real Estate |
| Covivio SA | France | Real Estate |
| Societe Fonciere Lyonnaise | France | Real Estate |
| Gecina SA | France | Real Estate |
| Icade | France | Real Estate |
| Klepierre SA | France | Real Estate |
| Mercialys SA | France | Real Estate |
| Nexity SA | France | Real Estate |
| Unibail-Rodamco SE | France | Real Estate |
| alstria office REIT-AG | Germany | Real Estate |
| Deutsche EuroShop AG | Germany | Real Estate |
| Deutsche Wohnen SE | Germany | Real Estate |
| LEG Immobilien AG | Germany | Real Estate |
| TAG Immobilien AG. | Germany | Real Estate |
| Grand City Properties SA | Luxembourg | Real Estate |
| CPI Property Group S.A. | Luxembourg | Real Estate |
| Eurocommercial Properties N.V. | Netherlands | Real Estate |
| Wereldhave N.V. | Netherlands | Real Estate |
| Olav Thon Eiendomsselskap ASA | Norway | Real Estate |
| Inmobiliaria Colonial SOCIMI, S.A. | Spain | Real Estate |
| Atrium Ljungberg AB (publ) | Sweden | Real Estate |
| Fastighets Balder AB | Sweden | Real Estate |
| Castellum AB (publ) | Sweden | Real Estate |
| Fabege AB (publ) | Sweden | Real Estate |
| Hufvudstaden AB (publ) | Sweden | Real Estate |
| Kungsleden Aktiebolag | Sweden | Real Estate |
| Klovern AB | Sweden | Real Estate |
| Wallenstam AB (publ) | Sweden | Real Estate |
| Wihlborgs Fastigheter AB | Sweden | Real Estate |
| PSP Swiss Property AG | Switzerland | Real Estate |
| Swiss Prime Site AG | Switzerland | Real Estate |
| Assura PLC | United Kingdom | Real Estate |
| F&C Commercial Property Trust Ltd | United Kingdom | Real Estate |
| British Land Company Plc | United Kingdom | Real Estate |
| Big Yellow Group PLC | United Kingdom | Real Estate |

**Table A1 (Cont.).** List of financial firms in the sample.

| Firm name | Country | Industry group |
|---|---|---|
| Capital & Counties Properties PLC | United Kingdom | Real Estate |
| CLS Holdings PLC | United Kingdom | Real Estate |
| Daejan Holdings PLC | United Kingdom | Real Estate |
| Derwent London PLC | United Kingdom | Real Estate |
| Great Portland Estates PLC | United Kingdom | Real Estate |
| Grainger PLC | United Kingdom | Real Estate |
| Hammerson PLC | United Kingdom | Real Estate |
| Intu Properties PLC | United Kingdom | Real Estate |
| Land Securities Group PLC | United Kingdom | Real Estate |
| LondonMetric Property PLC | United Kingdom | Real Estate |
| NEPI Rockcastle PLC | United Kingdom | Real Estate |
| NewRiver REIT PLC | United Kingdom | Real Estate |
| Safestore Holdings PLC | United Kingdom | Real Estate |
| Segro PLC | United Kingdom | Real Estate |
| Shaftesbury PLC | United Kingdom | Real Estate |
| St. Modwen Properties PLC | United Kingdom | Real Estate |
| Savills PLC | United Kingdom | Real Estate |
| UK Commercial Property Trust Ltd | United Kingdom | Real Estate |
| The Unite Group plc | United Kingdom | Real Estate |
| Workspace Group PLC | United Kingdom | Real Estate |
| Ackermans & Van Haaren NV | Belgium | Diversified Financials |
| Groupe Bruxelles Lambert SA | Belgium | Diversified Financials |
| Wendel SE | France | Diversified Financials |
| Eurazeo SE | France | Diversified Financials |
| Deutsche Boerse AG | Germany | Diversified Financials |
| Deutsche Bank AG | Germany | Diversified Financials |
| Grenke AG | Germany | Diversified Financials |
| Mediobanca SpA | Italy | Diversified Financials |
| Exor N.V. | Netherlands | Diversified Financials |
| Aker ASA | Norway | Diversified Financials |
| Axactor AB | Norway | Diversified Financials |
| Bolsas y Mercados Espanoles | Spain | Diversified Financials |
| Industrivarden AB | Sweden | Diversified Financials |
| Intrum AB | Sweden | Diversified Financials |
| Investor AB | Sweden | Diversified Financials |
| Kinnevik AB | Sweden | Diversified Financials |
| Investment AB Latour | Sweden | Diversified Financials |
| L E Lundbergforetagen AB | Sweden | Diversified Financials |
| Julius Baer Group Ltd. | Switzerland | Diversified Financials |
| Credit Suisse Group | Switzerland | Diversified Financials |
| GAM Holding AG | Switzerland | Diversified Financials |
| Pargesa Holding SA | Switzerland | Diversified Financials |

**Table A1 (Cont.).** List of financial firms in the sample.

| Firm name | Country | Industry group |
|---|---|---|
| Partners Group Holding AG | Switzerland | Diversified Financials |
| UBS Group AG | Switzerland | Diversified Financials |
| 3i Infrastructure PLC | United Kingdom | Diversified Financials |
| Ashmore Group PLC | United Kingdom | Diversified Financials |
| Alliance Trust PLC | United Kingdom | Diversified Financials |
| Baillie Gifford Japan Trust Plc | United Kingdom | Diversified Financials |
| Brewin Dolphin Holdings PLC | United Kingdom | Diversified Financials |
| Close Brothers Group PLC | United Kingdom | Diversified Financials |
| Caledonia Investments PLC | United Kingdom | Diversified Financials |
| Edinburgh Dragon Trust Plc | United Kingdom | Diversified Financials |
| Man Group PLC | United Kingdom | Diversified Financials |
| GCP Infrastructure Investments Ltd | United Kingdom | Diversified Financials |
| Hargreaves Lansdown PLC | United Kingdom | Diversified Financials |
| Intermediate Capital Group PLC | United Kingdom | Diversified Financials |
| IG Group Holdings PLC | United Kingdom | Diversified Financials |
| 3i Group PLC | United Kingdom | Diversified Financials |
| Investec PLC | United Kingdom | Diversified Financials |
| IP Group PLC | United Kingdom | Diversified Financials |
| JPMorgan Japanese Investment Trust Plc | United Kingdom | Diversified Financials |
| Jupiter Fund Management PLC | United Kingdom | Diversified Financials |
| London Stock Exchange Group PLC | United Kingdom | Diversified Financials |
| NEX Group PLC | United Kingdom | Diversified Financials |
| Provident Financial PLC | United Kingdom | Diversified Financials |
| Rathbone Brothers PLC | United Kingdom | Diversified Financials |
| RIT Capital Partners PLC | United Kingdom | Diversified Financials |
| The Scottish Investment Trust PLC | United Kingdom | Diversified Financials |
| Schroders PLC | United Kingdom | Diversified Financials |
| St. James's Place plc | United Kingdom | Diversified Financials |
| Syncona Ltd | United Kingdom | Diversified Financials |
| TP ICap PLC | United Kingdom | Diversified Financials |