The current issue and full text archive of this journal is available on Emerald Insight at:
https://www.emerald.com/insight/1526-5943.htm

Received 29 April 2024
Revised 24 September 2024
14 October 2024
Accepted 14 November 2024

A multi-period model for assessing the reinforcing dependence between climate transition and physical risks of non-life insurers

Onur Özdil
School of Business, Economics and Society,
Friedrich-Alexander-Universität Erlangen-Nürnberg, Nürnberg, Germany

Abstract

Purpose – Climate risks are crucial for non-life insurers due to their significant exposure to both transition and physical risks. The aim of this study is to develop a multi-period model that represents climate risks in non-life insurance, encompassing the impacts of both physical and transition risks as well as their reinforcing dependence. Literature suggests that as physical climate risks increase, the urgency for climate policies intensifies, leading to higher climate transition risks.

Design/methodology/approach – Our model includes a stochastic transition process affecting assets based on their exposure in climate policy-relevant sectors (green and brown investments) and a dependence structure between this process and liabilities, where the physical risks manifest as an increase in claims.

Findings – Our simulation indicates that the choice of the transition process, as well as the consideration of dependencies, has a significant influence on the insurers' profit, but even more on the probability of ruin. The impact of green versus brown investment strategies varies considerably based on whether dependencies are taken into account or not.

Originality/value – The results of this study are intended to deepen the understanding of the effects of climate risks on non-life insurers and provide a quantitative analysis of the impact of green and brown investing within this framework.

Keywords Climate risk, Non-life insurance, Stochastic modeling, Asset-liability management

Paper type Research paper

1. Introduction

"Once climate change becomes a defining issue for financial stability, it may already be too late" (Carney, 2015, p. 4). This statement highlights the significant challenges that climate change and its associated risks pose to the insurance industry, which need to be addressed proactively. Non-life insurers, unlike life insurers, face direct exposure to climate-related physical risks like extreme weather events, making their insurance portfolios vulnerable to environmental shifts. As a benchmark, figures from Swiss Re (2024) indicate an average annual increase in inflation-adjusted losses from natural catastrophes of 5.9% since 1994, reaching 108 billion USD in 2023. Their short-term contracts not only allow for frequent re-pricing, offering flexibility, but also require constant vigilance to adapt to evolving climate trends. As key actors in ensuring financial stability, non-life insurers play a critical role in managing and mitigating the systemic risks posed by climate change.

Direct impacts from physical climate risks (e.g. natural disasters) are already affecting the insurance industry, whereas the consequences of transition risks linked to policy changes, such as emission reduction efforts, disrupting technologies and changes in customer preferences

JEL Classification — C51, G22, G32, Q54

The Journal of Risk Finance
Vol. 26 No. 1, 2025
pp. 98-121
Emerald Publishing Limited
1526-5943
DOI 10.1108/JRF-04-2024-0121

remain less clear (ECB, 2021). Moreover, the economic uncertainties stemming from transition risks surpass geophysical uncertainties tied to physical risks by far (Nordhaus, 2018). While transition risks concern the entire insurance industry as an institutional investor, physical risks are particularly significant for the liabilities of non-life insurers (EIOPA, 2022a). In this regard, both EIOPA (2022b) and the German financial supervisory authority BaFin (2019) underline the importance of conducting an in-depth evaluation of both climate transition and physical risks, while also considering the interdependencies between these risks. The European Central Bank (2021) emphasizes the lack of research and methodologies that integrate evaluations of both physical and transition risks with possible interactions between them.

In the short term, an interaction between those risks refers to the dynamic relationship wherein increased physical climate risks, such as the occurrence of climate-related natural disasters, heighten awareness and underline the urgency of climate protection policies. Campiglio *et al.* (2023) highlight that the main concern in the context of climate risks is an abrupt transition of the economy following climate-related physical disasters. Also, changes in market sentiment, triggered by recognition of potential, yet to materialize climate risks, could trigger considerable economic shocks (University of Cambridge Institute for Sustainability Leadership CISL, 2015). Gaudemet *et al.* (2022) describe in their model framework a positive correlation between physical and transition risk in the case of positive transition efforts due to the reactivity of these efforts to climate change. An example of a swift and decisive response to natural catastrophes can be seen in the 2003 European heatwave, which resulted in over 70,000 deaths. This event encouraged European governments to implement stronger climate adaptation measures, improve heatwave preparedness and accelerate renewable energy promotion (Parry *et al.*, 2007). Should one or more natural disasters occur in the future that are widely regarded as a direct result of climate change, it could lead to severe market reactions and an immediate implementation of strict climate policies, mirroring these past responses (Vermeulen *et al.*, 2018). This emphasis, in turn, would reinforce climate transition risks and reduce the value of investments relevant to climate policies, leading to a simultaneous shock on both assets and liabilities of non-life insurers. In the long term, an intertemporal trade-off exists. Early climate mitigation actions can decrease future physical risks, but this impact is anticipated to manifest in the second half of the 21st century (IAA and IPCC WGI, 2022, p. 21).

Concerning transition risks, there are various methodological approaches for assessing their impact on asset portfolios. Weyzig *et al.* (2014) investigate the impact of a so-called carbon bubble shock on the asset portfolios of banks and pension funds, in which a rapid transition leads to, for example, 60% equity losses and 30% bond losses in oil, gas and coal companies. Another top-down approach to examining the impact of transition risks on asset portfolios is demonstrated by Vermeulen *et al.* (2018), which, among other things, attempts to assess the impact of a policy shock (an increase in the CO_2 price by 100 euros per ton) on the assets of insurers, resulting in a loss of 8–10% of the assets. A similar approach was adopted during the 2022 stress test of Institutions for Occupational Retirement Provision (IORP) by EIOPA (2022c), in which an immediate transition, triggered by an increase in the CO_2 price by 321 euros per ton, reduced the value of assets by an average of 12.9% (EIOPA, 2022d). However, the assumption of an immediate transition is rather unrealistic, and it is expected that a transition to a low-carbon economy would unfold over several years. Roncoroni *et al.* (2021) introduced stochasticity within the transition process in order to perform a cost-benefit analysis in this context, but their approach was binary in nature – a transition either took place or did not, and if it did, it was orderly or disorderly with a certain probability. Notably, their work did explicitly not focus on annual transition progress or estimating these probabilities. Desnos *et al.* (2023) focus on modeling transition risk for asset portfolios by incorporating a stochastic carbon price and introducing mechanisms to address potential financial effects. In contrast to Desnos *et al.* (2023), a more comprehensive approach is adopted in this paper that considers the potential to achieve the Paris Climate Agreement goals beyond the carbon price mechanism, such as subsidies for renewable energy systems and comparable policy measures (Gillingham and Stock, 2018), and explicitly utilizes potential asset losses already identified from climate stress tests conducted in practice (EIOPA, 2022d).

In the context of modeling interactions between physical and transition risks, EIOPA (2022b) addresses the short-term nature of possible physical transition climate shock scenarios for the insurance industry. This scenario is further investigated by Gatzert and Özdil (2024) on an annual basis, applying a modeling approach and a quantitative scenario analysis for climate risks in non-life insurance. In their analysis, the transition is instantaneous, as described by EIOPA (2022c), with the scenario analysis having a time horizon of one year. However, it is obvious that a complete transition to climate neutrality, including the associated market effects, cannot be achieved in a single major step within a year but will unfold over the coming decades (Milkau, 2022). This makes it essential to incorporate a short- to medium-term time horizon when assessing and modeling climate transition risks.

Gatzert and Özdil (2024) also exclusively consider negative impacts on so-called brown investments related to transition risks, without assessing potential positive effects on so-called green assets. Recent studies show that, in the context of the transition to a lower-carbon economy, green assets can significantly benefit in the short and medium term compared to brown assets (see, e.g. Ardia *et al.*, 2023; Bolton and Kacperczyk, 2023; Campiglio *et al.*, 2023), which makes the inclusion of such effects essential for a comprehensive risk assessment. The investigation of potentially reinforcing dependencies between transition and physical climate risks for non-life insurers over multiple periods, particularly in the short- to medium-term horizon, has so far received little attention in academic literature. Therefore, it is all the more important to advance research in risk assessment for non-life insurance through short- to medium-term modeling approaches that not only reflect the multifaceted influence of transition risks but also address potential dependencies between these and physical risks.

With this in mind, this paper introduces a model for evaluating both climate transition and physical risks, as well as their potential dependencies, over multiple periods until 2050 within the context of a non-life insurer. We expand existing studies and methodologies regarding the impact of climate transition risks by introducing a stochastic transition process, which measures the progress towards the target of limiting global warming to 2°C until 2050, and connecting this process to the risk model of a non-life insurer. The influence of the transition process on portfolio return rate is dependent on the portfolio composition, specifically on the proportion of green and brown investments. Additionally, we integrate physical climate risks using exponential regression of global inflation-adjusted insured losses and extrapolation until 2050. This allows us to apply a reinforcing dependence between physical and transition risks, where high transition risks occur more likely with high physical risks. This idea is based on the insights from Gatzert and Özdil (2024) and involves nonlinear dependence structures (copulas) with tail dependencies between assets and liabilities. However, we extend their approach in two ways. First, we account for a short- to medium-term time horizon rather than an instantaneous transition. Second, we do not only focus on the negative effects of brown assets, but also consider the positive effects of green assets. Even though the quantitative results in this paper are primarily based on the European region, the model has potential applicability to other countries that have joined the Paris Climate Agreement and committed to a lower-carbon economy. However, its transferability to non-European and less developed economies may require further research to account for specific regional and economic factors. The model presented in this paper serves as an additional methodological component for modeling the impact of climate risks – depending on the geographical exposure to physical climate risks and economic exposure to transition risks – on the financial sector, and could be used by both regulatory authorities and companies as part of their climate risk management frameworks.

Depending on the distribution of the transition process – which implicitly addresses the risk of a disorderly transition – we observe that both transition risks, and importantly, the dependence between physical and transition risks, can significantly impact the balance sheets of non-life insurers. While the influence on profit becomes more pronounced as the time horizon extends, for shorter time horizons, the impact on ruin probability is already significant. Additionally, the impact of browner or greener investment strategies is contingent upon whether the reinforcing dependence is taken into account or not.

The remainder of this paper is structured as follows. Section 2 describes the model framework for a non-life insurer, numerical results are presented in Section 3, and Section 4 concludes.

2. Model framework

Our risk model of a non-life insurer is based on a discrete-time surplus process U_n, $n \in \{n_0, \ldots, N\}$ with portfolio return rate r_n, claims S_n and corresponding premium income π_n of the following form:

$$U_n = (1 + r_n) \cdot (U_{n-1} + \pi_n) - (S_n - S_{n-1}), U_{n_0} = E_0, \tag{1}$$

where $S_n - S_{n-1}$ denotes the annual claims in year n and E_0 the initial equity (see, e.g. Eckert and Gatzert, 2018; Gatzert and Özdil, 2024).

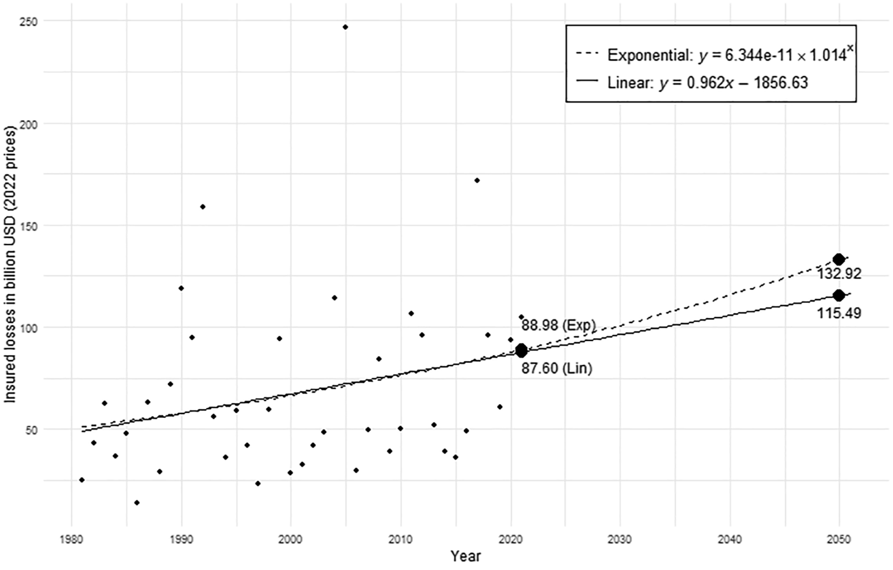
2.1 Physical risks

Physical climate risks, inherently multifaceted and varying across regions, countries and climate conditions, pertain to the potential financial losses stemming from climatic changes. They manifest in two main forms: acute risks from extreme weather events, like floods or storms, and chronic risks stemming from long-term climate pattern shifts, such as rising sea levels or persistent temperature changes (EIOPA, 2022e). These risks can lead to tangible economic impacts, affecting asset value, operational costs and insurance claims. Milkau (2022) emphasizes that while Europe might perceive its physical climate risks as manageable, the more pronounced impacts in regions like Asia and Africa could have consequential spillover effects on Europe (Milkau, 2022). In these regions, physical risks even affect effective labour productivity and thus affect the countries' GDP more severely than in Europe (Dasgupta *et al.*, 2021). Milkau (2022) also states that extreme climate events have a nonlinear relation to economic damages, since only 3% of extreme events were responsible for around 60% of losses. This relation to extreme events is even less linear to finance institutions' balance sheets. Therefore, it is evident that physical climate risks have a global impact, even if their direct influence can vary regionally.

For a non-life insurer, the physical climate risk exposure is mainly driven by increasing catastrophic losses (EIOPA, 2022b) and is expected to affect all property-related lines of business (EIOPA, 2022e). The repercussions of climate change are already evident today, especially in certain regions and within the insurance industry. EIOPA (2021) states that expected annual flood claims are projected to increase by 34–75% in 2050. Similar estimates can be found in the Bank of England (2022) climate biennial exploratory scenario, where an increase of average annualized losses for general insurers by around 50–70% in 2050 is projected, and in Climate Analytics (2024), in collaboration with, among others, the Network for Greening the Financial System (NGFS), where in the case of annual flood damage in Germany, depending on the scenario considered, an increase in the median by 2050 of between 32% and 86% is expected. Dionne and Desjardins (2022) demonstrate through an empirical study that, although insurers' capacity to bear catastrophe risks has significantly increased due to rising available capital since 1997, the ability to adequately insure against future catastrophe risks remains problematic. In our model, the annual claims amount $(S_n - S_{n-1})_{n \in \{n_0, \ldots, N\}}$, which is primarily affected by physical risks, is assumed to follow a lognormal distribution $\mathcal{LN}(m_n, v_n)$. This assumption aligns with Burnecki *et al.* (2000), who identified a good fit of the lognormal distribution for Property Claim Services (PCS) indices representing insured catastrophic losses in the United States. The parameters m_n and v_n of the lognormal distribution are uniquely determined by the mean μ_n and standard deviation σ_n of the distribution by

$$m_n = \ln\left({\mu_n}^2 \Big/ \sqrt{{\sigma_n}^2 + {\mu_n}^2}\right) \text{ and } v_n = \ln\left(1 + \left({\sigma_n}^2 / {\mu_n}^2\right)\right).$$

Since the aim of this paper is to model dependencies between physical and transition risks and to investigate their influence on corporate metrics, and particularly not to study an exact prediction for the behavior of physical claims, we will introduce a rather simple approach for our model framework. Here, we will use historical data on insured losses to predict future claim trends. We therefore apply linear and exponential extrapolation techniques to global inflation-adjusted insured losses in order to assess physical climate risks (see Figure 1). Exponential regression of given data points $(n, y_n)_{n\in\{n_0,\ldots,N\}}$ by a general exponential function $y = a \cdot b^n$ is performed by applying linear regression to the transformed data $(n, \ln(y_n))_{n\in\{n_0,\ldots,N\}}$ to determine a line of the form $\ln(y) = m \cdot n + c + \epsilon$ by minimizing the correction term ϵ. The coefficients of the exponential function are then determined by $a = e^c$ and $b = e^m$. The resulting exponential regression function $y = a \cdot b^n$ can then be used for extrapolating expected insured losses into the future. Analyzing the extrapolations illustrated in Figure 1, with the reference year being 2022, reveals a projected increase in insured losses up to 2050, with an estimated growth of 49.4% under exponential extrapolation, which aligns with the lower range of Bank of England (2022), and 31.8% under linear extrapolation, which aligns with the lower range of EIOPA (2021). The data for this regression illustrated in Figure 1 are based on global damage data from Swiss Re (2023), each discounted using global inflation rates from the World Bank (2023). To predict the distribution parameters for future years in our model, we assume that the expected value of the damages μ_n will evolve according to the exponential regression function $\mu_n = a \cdot b^n$, whereby the resulting relative increase by 2050 is



Source(s): Swiss Re (2023); World Bank (2023)

Figure 1. Linear and exponential extrapolations of inflation-adjusted global insured losses, 1981–2021, projected through 2050

comparable to estimates in various studies (see, e.g. Bank of England, 2022; Climate Analytics, 2024; EIOPA, 2021).

In order to incorporate physical climate risks into both distribution parameters of claims, we make an additional assumption beyond the progression of expected claims μ_n. Specifically, we introduce the assumption that the coefficient of variation

$$c_v = \frac{\sigma_n}{\mu_n}, \forall n \in \{n_0, \ldots, N\} \Leftrightarrow \sigma_n = \mu_n \cdot c_v, \forall n \in \{n_0, \ldots, N\} \tag{2}$$

remains constant. This assumption is also suggested by GDV (2023) for extrapolating claims in the context of climate change. This enables us to extrapolate the standard deviation σ_n of the claims distribution by fixing the coefficient of variation c_v and extrapolating the mean of claims μ_n.

Coupled with the surge in insurance claims, we assume that risk-based insurance premiums increase due to the increasing intensity of climate risks. This might impact the affordability and accessibility of insurance policies covering climate-related risks (EIOPA, 2023). The issues of underinsurance and the lack of availability, stemming from affordability challenges in areas with high risk, present a case against the adoption of premiums based on risk as well as against a solely private sector-based insurance model (Lucas and Booth, 2020). Hence, the assumption of risk-based premium income in the context of climate risks first requires critical reflection. In the United States, there exists a notable system of cross-subsidization among states when it comes to insurance premiums related to climate risks. Drawing from the study by Oh *et al.* (2022), U.S. states less affected by physical climate risks, and with more relaxed premium regulations, indirectly cover the costs for those states that face greater climate threats and have stricter pricing regulations. This phenomenon is primarily driven by the mediating effect of pricing regulations, causing premiums to not fully reflect the extent of physical climate risks. As a result, households in states with fewer climate-related concerns end up financially supporting, through their premiums, those in high-risk states. So, even as climate risks intensify, such cross-subsidizations can ensure that risk-based premiums remain a feature, even though with modifications in how they are applied (Lamond and Penning-Rowsell, 2014). Therefore, applying the principle of pricing based on standard deviation, we posit that the risk-based premium income in year n corresponds to the expected claims from the same year along with the standard deviation of claims with the latter being adjusted by a loading constant $\delta > 0$, i.e.

$$\pi_n = \mu_n + \delta \cdot \sigma_n. \tag{3}$$

In this paper, the impact of reinsurance is not examined. Gatzert and Özdil (2024) demonstrate that stop-loss reinsurance can be an effective risk transfer tool for mitigating physical climate risks for non-life insurers, but it is less effective for addressing transition risks. Furthermore, it has minimal impact on the potential interdependencies between physical and transition risks, both of which – transition risks and their interdependencies – are the main focus of this paper. However, the availability and affordability of suitable reinsurance instruments have not been guaranteed in recent times, which is why alternative risk transfer mechanisms, such as Insurance-Linked Securities, are becoming increasingly important and gaining market share (Ben Ammar *et al.*, 2015). Therefore, the role of reinsurance structures with regard to physical climate risks is a central subject of current research (see, e.g. Lehtonen, 2017; Tesselaar *et al.*, 2020), but is beyond the scope of this paper.

2.2 Transition risks

The effects of transition risks include shocks caused by changes in climate mitigation and adaptation policies, reputational impacts, shifts in market preferences and technological innovation (Bolton and Kacperczyk, 2023; Campiglio *et al.*, 2023). The impact on assets is therefore primarily driven by market and credit risks (EIOPA, 2022b). Market risks arise from the potential devaluation of financial assets due to the transition to a low-carbon economy. This includes scenarios of stranded assets [1] and decreased market values in sectors heavily dependent on carbon-intensive activities. Credit risks come into play when counterparties experience a decline in creditworthiness, particularly among companies inadequately prepared for transition risks. Both types of risks can lead to negative impacts on insurers' asset values through equity price or yield shocks, as outlined by EIOPA (2022b). By focusing on transition risks, we first need to consider the time frame in which a transition to climate-neutral economy is expected to happen. A consensus in recent studies suggests that such a transition is unlikely to occur in a single, massive shift within a year but is more likely to unfold gradually over the next few decades (EIOPA, 2022c; Milkau, 2022).

Instead of evaluating transition risks based on the possibility of an immediate transition, whether orderly or disorderly, our paper employs an approach distinct from that described in Roncoroni *et al.* (2021). We quantify climate protection measures on a scale from 0 to 1. Here, 0 signifies the current status quo, while 1 indicates full compliance with the Paris Climate Agreement and the goal of limiting global warming to 2°C. Despite instances where individual countries have backtracked in their transition efforts in certain years, such as the withdrawal of the United States from the Paris Agreement in 2017, the current policies scenario in the latest NGFS Scenario Explorer – which represents the worst-case scenario for transition efforts – indicates that global annual emissions will not increase significantly through 2050 (NGFS, 2024). This means that on a global basis, it can be assumed that the annual transition steps are positive. Building on this, we introduce a monotonically increasing stochastic transition process $(t_n)_{n\in\{n_0,\ldots,N\}} \geq 0$, which defines the total efforts to limit global warming to 2°C until the year n. For instance, a value of $t_{n_0+1} = 1$ would indicate that all necessary efforts to limit global warming to 2°C were accomplished in the first year. Conversely, $t_N = 0$ indicates that by year N, no efforts towards this goal have been initiated. Building on this, we assume that the expected transition progress in year n ($\mathrm{E}[t_n - t_{n-1}|t_{n-1}]$), conditional on the previous state of the transition progress in year $n-1$, corresponds to the average annual increment if the same step were taken every year from year n until year N, with the transition process t_N reaching 100% in year N:

$$\mathrm{E}[t_n - t_{n-1}|t_{n-1}] = \max\left(\frac{1 - t_{n-1}}{(N+1) - n}, 0\right), t_{n_0} = 0. \tag{4}$$

Additionally, we assume that the transition process has an upper bound at 1 and thus stops as soon as 100% of the necessary climate protection measures have been taken by year $\widetilde{n}$

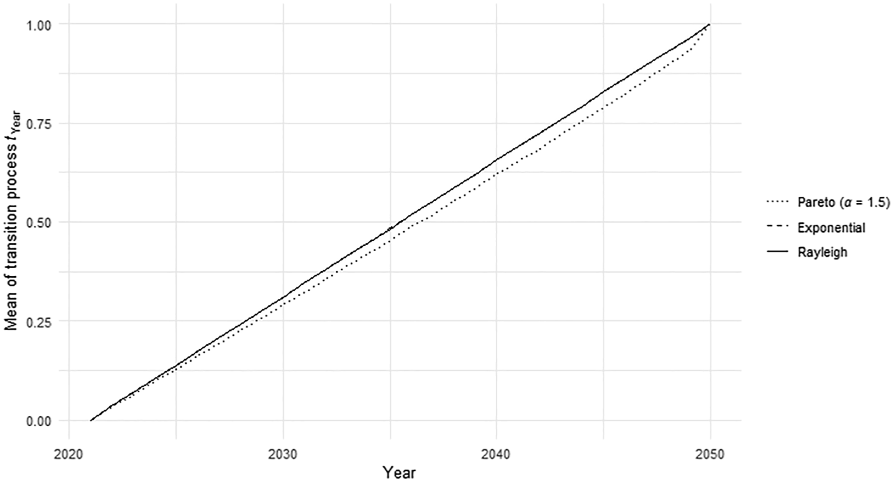
$$\min\left(t_{\tilde{n}}, 1\right) = 1 \Rightarrow t_n = 1, \forall n \in \left\{\widetilde{n}, \ldots, N\right\}.$$

Based on this characteristic, we observe that for the smaller values of n, the probability of large annual transition steps is higher, as the upper bound for possible annual transition progress $t_n - t_{n-1}$ decreases monotonically. This aligns with the consideration that the risk of a disorderly transition, characterized by a higher probability of large shifts, is particularly significant in the upcoming decade. Notably, the likelihood of these substantial transition steps diminishes over time, which is in line with the disorderly transition 2030 scenario outlined in NGFS (2022).

Furthermore, we incorporate various types of distributions for the annual transition progress, encompassing thin-tailed, medium-tailed and heavy-tailed distributions (Nordhaus, 2011). Specifically, we examine the Rayleigh, exponential and Pareto distribution ($\alpha = 1.5$), as they pertain to our analysis. In the context of this paper, the selection of these three distributions results in distinct temporal evolution patterns for the transition process. For instance, by considering the distribution of the first annual transition progress t_{n_0+1} with expected value $1/(N-n_0)$ according to Equation (4), we see a standard deviation of $\pi^{-1/2}/(N-n_0)$ for Rayleigh-distributed, $1/(N-n_0)$ for exponentially distributed and an infinite variance for Pareto-distributed transition process neglecting the upper bound of 1. However, since the transition process stops once 100% is reached, the standard deviation for the Pareto distribution is approximately $1.7/(N-n_0)$ when simulated. By focusing on the simulated means of these transition processes depending on the underlying distribution, we observe that the means consistently follow the linear trendline, as shown in Figure 2. The mean of Pareto-distributed transition paths stands out as an exception, positioning slightly below the trendline due to their theoretically infinite variance, but upper-limited value range.

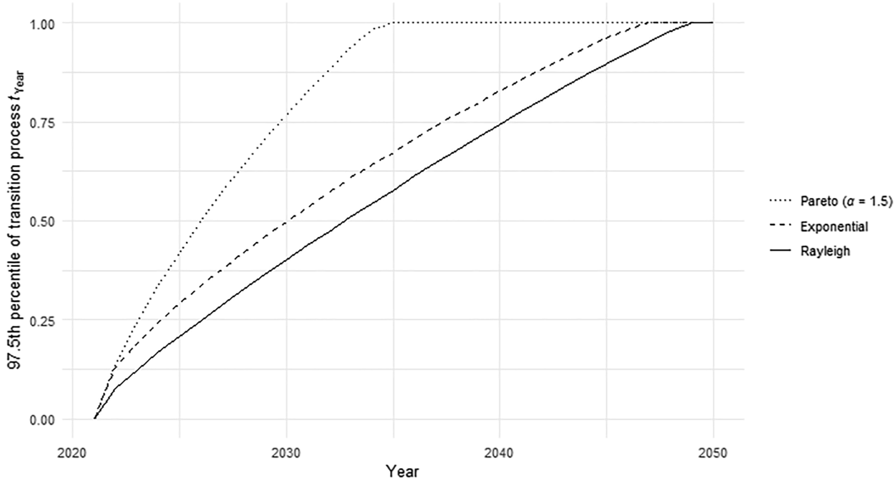
However, when we examine the quantiles of the transition process under these distributions, specifically the 97.5th percentile, a contrasting picture emerges, see Figure 3. While the 97.5th percentile of the thin-tailed Rayleigh-distributed transition process closely follows the linear trendline, a fatter tail leads to the 97.5th percentile reaching 100% transition more quickly over time. For a transition process characterized by a Pareto distribution, a complete transition is achieved by 2035 for the most adverse 2.5% of scenarios. In contrast, for an exponentially distributed transition process, this critical juncture is not reached until 2047, and for one governed by a Rayleigh distribution, it extends to 2049. These findings highlight the significance of distribution choice in understanding the temporal dynamics of the transition process, particularly when assessing extreme outcomes. Heavy-tailed properties of the Pareto distribution address the risk of a sudden and disorderly transition by 2030 implicitly, since the likelihood of greater transition steps is notably higher under heavy-tailed distributions than in distributions with thinner tails.

In the following, we will examine how the transition process and the associated transition risks specifically impact capital investments in this context. Campiglio *et al*. (2023) found that "brown" assets, which have a negative response to climate risks and signify a heightened vulnerability to the downsides of transitioning away from practices like fossil fuel use, typically face adverse effects. These can range from reduced value and heightened risk evaluations to increased capital costs. On the other hand, "green" assets, which are aligned with low-carbon strategies such as renewable energy production and thus are expected to benefit from a low-carbon transition, present different outcomes (Campiglio *et al*., 2023). In the literature, this issue is also referred to as carbon premium (Alessi *et al*., 2021; Bolton and Kacperczyk, 2023). Battiston *et al*. (2017) devised a categorization of economic activities within climate-policy-relevant sectors based on the NACE Rev2 standard [2]. This classification indicated that approximately 8.3% of the total assets of pension funds were



Source(s): Author's own work

Figure 2. Temporal development of the arithmetic mean for a Pareto- ($\alpha = 1.5$), exponentially and Rayleigh-distributed transition process according to Equation (4) with one million random pathways



Source(s): Author's own work

Figure 3. Temporal development of the 97.5th percentile for a Pareto- (α = 1.5), exponentially and Rayleigh-distributed transition process according to Equation (4) with one million random pathways

directly linked to these sectors. These sectors are characterized by their substantial sensitivity to transition risks, which can have both positive and negative impacts on their revenues. This classification has been adopted for assessing the impact of climate risks on asset portfolios by financial supervising institutions (EIOPA, 2022c). In line with this, the 2022 European climate stress test for pension funds revealed significant drops in brown assets, from 15% for non-metallic mineral corporate bonds to 37.5% for mining equity, with other investments also experiencing an average loss of around 12.4% (EIOPA, 2022d).

Based on these considerations, we have categorized our asset portfolio with the corresponding return rate r_n according to Equation (1) into three distinct subportfolios: "brown," "green" and "other". This approach builds upon the framework of Gatzert and Özdil (2024), with the addition of a "green" subportfolio. We assume that the annual portfolio return rate r_n in year n follows a normal distribution $\mathcal{N}(\mu_r, \sigma_r)$ and is determined by a convex combination, represented by the following equation:

$$r_n = q^{Brown} \cdot r_n^{Brown} + q^{Green} \cdot r_n^{Green} + \left(1 - q^{Brown} - q^{Green}\right) \cdot r_n^{Other}. \tag{5}$$

For the sake of simplicity, we assume that the portfolio composition remains constant over time. In this context, both q^{Brown} and q^{Green} denote the proportions of the portfolio invested in climate policy-relevant sectors. They are presumed to either suffer (brown) or benefit (green) from the transition, respectively (Bank of England, 2022; EIOPA, 2022d).

According to the current state of the literature, it is evident that brown assets are adversely affected in terms of asset price and capital costs, i.e. they experience higher capital costs and lower valuation and returns (Campiglio *et al.*, 2023). The Institutions for Occupational Retirement Provision (IORP) stress test described in EIOPA (2022d) revealed that corporate bonds and stocks in sectors such as mining, petroleum, non-metallic mineral, electricity and land transport would be particularly negatively impacted by a transition. Furthermore, there are studies underlining the hypothesis that an unexpected increase in climate change concerns leads to decreasing and increasing valuation of brown and green firms, respectively (Ardia *et al.*, 2023). Recent studies support this notion, indicating the emergence of physical and transitional climate risk premiums (see, e.g. Bolton and Kacperczyk, 2023; Bua *et al.*, 2022). This suggests that higher returns are asked for stocks that poorly hedge against climate risks, subsequently raising the cost of capital for such companies.

Regarding green assets, such as those that currently do not pay a carbon price or are not affected by the EU Emission Trading System, the current state of the literature shows a positive impact on asset prices, capital costs and risk (Campiglio *et al.*, 2023). For example, In *et al.* (2019) demonstrate that carbon-efficient firms outperform carbon-inefficient ones by an annual return margin ranging from 3.4% to 5.4%. Similar results were also obtained by Ravina and Hentati-Kaffel (2020), who found a significant outperformance of green stocks compared to brown stocks in Europe between 2008 and 2018. Therefore, in this context, we assume that the value of green assets receives a positive shock through the transition process.

We furthermore assume that return rates of brown, green and other subportfolios follow a normal distribution, whose distribution parameters μ_r and σ are independent of the carbon sensitivity of the corresponding assets, following EIOPA (2022f, p. 61). To link the externally specified transition process to our risk model of a non-life insurer, we posit that transition risk directly corresponds to our transition process $(t_n)_{n\in\{1,..,N\}}$. We assume that the annual transition progress $(t_n - t_{n-1})$ determines the extent of the "full transition shock" for a particular asset class in year n. Similar to Battiston and Monasterolo (2021) and EIOPA (2022f), we therefore assume partial annual shocks on the return rates of brown, green and other subportfolios in the following way:

$$\begin{aligned} r_n^{Brown} &\sim \mathcal{N}\left(\mu_r - (t_n - t_{n-1}) \cdot FTS^{Brown}, \sigma\right), \\ r_n^{Other} &\sim \mathcal{N}\left(\mu_r - (t_n - t_{n-1}) \cdot FTS^{Other}, \sigma\right), \\ r_n^{Green} &\sim \mathcal{N}\left(\mu_r + (t_n - t_{n-1}) \cdot FTS^{Green}, \sigma\right), \end{aligned} \tag{6}$$

where FTS^{Brown}, FTS^{Green} and FTS^{Other} denote the full transition shock for brown, green and other investments, respectively, which would occur in an instant transition to 2°C climate target compliant economy (EIOPA, 2022d, pp. 18). Owing to the stochastic nature of t_n, we obtain a stochastic expected value for all three return rates. To account for correlations between the individual returns, we define the multivariate normal distribution of the random vector $\boldsymbol{r_n} = (r_n^{Brown}, r_n^{Other}, r_n^{Green})$ with mean vector $\boldsymbol{\mu_n} = (\mu_r - (t_n - t_{n-1}) \cdot FTS^{Brown}, \mu_r - (t_n - t_{n-1}) \cdot FTS^{Other}, \mu_r + (t_n - t_{n-1}) \cdot FTS^{Green})$ and covariance matrix:

$$\Sigma = \sigma^2 \cdot \begin{pmatrix} 1 & \rho_{Brown,Other} & \rho_{Brown,Green} \\ \rho_{Brown,Other} & 1 & \rho_{Green,Other} \\ \rho_{Brown,Green} & \rho_{Green,Other} & 1 \end{pmatrix}. \tag{7}$$

The entries in the covariance matrix Σ divided by σ^2 represent the pairwise linear correlations between the three variables. In order to exclude diversification effects between the subportfolios, we fix the standard deviation of the overall portfolio σ_r and scale the standard deviation of the subportfolios by:

$$\begin{aligned} \sigma = \sigma_r \bullet (&q^{Brown^2} + q^{Green^2} + (1 - q^{Brown} - q^{Green})^2 + 2\rho_{Brown,Green} q^{Brown} q^{Green} \\ &+ 2\rho_{Brown,Other} q^{Brown} 1 - q^{Brown} - q^{Green} + 2\rho_{Brown,Other} q^{Green} (1 - q^{Brown} - q^{Green}))^{-\frac{1}{2}}. \end{aligned} \tag{8}$$

2.3 Reinforcing dependence between physical and transition risks

The recent literature often highlights an intertemporal trade-off between physical and transitional climate risks (Milkau, 2022; TCFD, 2017). Transition risks, related to climate mitigation costs, are believed to influence physical risks over a long timescale. An orderly or disorderly completion of a transition to a low-carbon economy is expected to decrease the costs of physical climate damage in the future significantly (TCFD, 2017). Zhao *et al.* (2020) suggest that by achieving the 2°C Paris Climate Target Goals, it is possible to reduce the expected aggregate global climate damage until 2100 from 518 trillion USD by 40–50%. But it should be noted that, up until 2050, all standard IPCC scenarios consistently project a global warming trend of 1.5°C, as documented by IAA and IPCC WGI (2022, p. 21). Consequently, within the time frame until 2050, we have chosen not to consider the effects of climate mitigation policies on long-term physical risk exposure and thus the intertemporal trade-off between physical and transition risks. These effects are anticipated to become more pronounced and impactful after the year 2050 (IAA and IPCC WGI, 2022).

In this paper, we focus on the influence of physical risks on transition risks, emphasizing the reinforcing interdependence between the two. Previous research shows that an unexpected increase in climate change concerns, through natural disasters, for instance, leads to decreasing and increasing valuation of brown and green firms respectively (Ardia *et al.*, 2023; Pástor *et al.*, 2021), which can be interpreted as an increase of transition risks. The German financial supervisory authority BaFin (2019) also points out that an increase in physical risk would require a more abrupt transition of the economy, leading to higher transition risks. This implies that the occurrence of acute and chronic physical climate risks, along with the increased climate risk awareness among investors, consumers and governments, is closely associated with a high degree of transition risks. Therefore, we assume that high physical risk in year n, i.e. occurrence of natural disasters, which are measurable in high claims of non-life insurers, leads to an increase in transition risks in the same year n. This assumption of a dependency structure is consistent with the findings of Gaudemet *et al.* (2022), which show that the correlation between physical and transition risk is positive, assuming an existing reactivity of transition efforts to climate change.

With this in mind and similar to Gatzert and Özdil (2024), we assume a positive dependence between the annual transition progress $t_n - t_{n-1}$ and the annual claims amount $S_n - S_{n-1}$ for every year n. In other words, high physical risks in year n, which materialize through high claims, lead to a larger expected transition step by increasing awareness of the adverse impacts of climate change. This, in turn, prompts not only heightened urgency for climate policies, but also drives technological innovation and shifts in customer preferences towards more sustainable products and services, further amplifying transition risks (Pástor *et al.*, 2021). Assuming a mutually reinforcing effect between transition risks and physical risks within a year deserves a brief explanation. Even if necessary climate protection measures are implemented with a time lag in the course of occurring climate events, the capital market and customer preferences usually anticipate more quickly in such cases, and with respect to stocks, as shown by Ardia *et al.* (2023), even immediately. If the market effects, regardless of the trigger, were to occur with a delay of, for example, one year instead of within the same year, the reinforcing dependence would have a significantly smaller impact on financial stability [3].

The unpredictability associated with climate change can lead to scenarios where rare but highly consequential events become more likely. This phenomenon, characterized as "tail fattening", emphasizes that our limited knowledge cannot always predict the full extent of damages, and this heightened uncertainty can have a significant economic impact (Weitzmann, 2009). Therefore, and similar to Gatzert and Özdil (2024), the reinforcing interdependence between physical risks and transition risks is represented by tail dependencies. We assume, that the annual transition progress $t_n - t_{n-1}$ is dependent on the annual claims $S_n - S_{n-1}$ and the dependence structure is given by a copula with upper tail dependence. The bivariate Clayton copula based on Clayton (1978) is thereby defined as

$$C_\theta^{Cl}(u_1, u_2) = max\left\{\left(u_1^{-\theta} + u_2^{-\theta} - 1\right)^{-1/\theta}, 0\right\}, u_1, u_2 \in [0, 1], \theta \in (0, \infty).$$

In this paper, we employ a 180° rotated Clayton copula for the dependence structures, aiming to achieve upper tail dependence rather than lower tail dependence, by following transformation:

$$C_\theta^{St}(u_1, u_2) = u_1 + u_2 - 1 + C_\theta^{Cl}(1 - u_1, 1 - u_2). \tag{9}$$

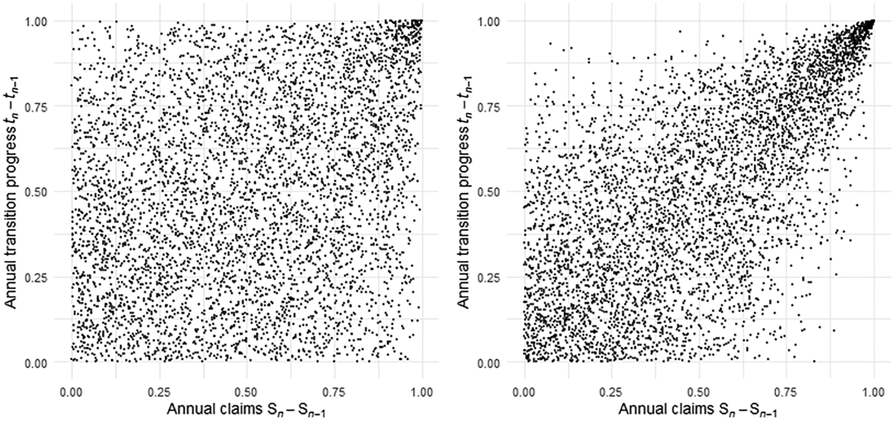
To visually illustrate this, Figure 4 shows random numbers from the copula described in Equation (9), from which it is evident that the strength of the dependence, and thus also the tail dependence, increases with the parameter θ. For standardization, Kendall's tau can also be calculated from the copula parameter theta using

$$\rho_\tau = \frac{\theta}{\theta + 2} \Leftrightarrow \theta = \frac{2 \cdot \rho_\tau}{(1 - \rho_\tau)}, \tag{10}$$

which we will use to conduct sensitivity analyses in Section 3.3. The dependence structure described by the above-mentioned copula in this context refers to the reactivity of transition efforts to the physical impacts of climate change and can therefore, analogously to Gaudemet *et al*. (2022), be considered constant over time.

2.4 Finite-time ruin probability and expected surplus

As shown in the previous chapters, climate risks have a highly multifaceted impact on the balance sheets of non-life insurers. In addition to the influence of physical climate risks on many lines of insurance business and liabilities, the influence of transition risks on investments – and thus on profitability – also comes into play. In this context, it is important not to overlook the impact that physical risks can have on assets such as real estate, and that transition risks can affect liabilities in the form of climate litigation risk (Bank of England, 2022). Together with the potentially reinforcing effect of both types of risks discussed in the previous Section 2.3, this strengthens the assumption of a significant potential impact, especially on stability and solvency, but also on profitability (EIOPA, 2022b). To assess the



Source(s): Author's own work

Figure 4. Simulation of 5,000 random numbers from the dependence describing copula C_θ^{St} ($\theta = 0.5$ on the left, $\theta = 2$ on the right) between annual transition progress $t_n - t_{n-1}$ and annual claims $S_n - S_{n-1}$

multi-year effects of both physical and transitional climate risks on the balance sheet, we consider key metrics such as the probability of ruin and expected surplus. The impact on solvency is measured by the finite-time ruin probability:

$$RP(n) = P\left(\min_{n_0 \le m \le n} \{U_m\} < 0\right). \tag{11}$$

This probability refers to the likelihood that the surplus according to Equation (1) becomes negative at least once within the time interval until n, indicating a situation where assets are insufficient to cover total claims. To assess the influence of physical and transition risks on profitability, EIOPA (2022a) also recommends exploring the cumulative effect on a company's profits (EIOPA, 2022a, b). Therefore, we examine the anticipated surplus as part of our analysis.

$$ES(n) = E[U_n], \tag{12}$$

where surplus U_n is defined according to Equation (1).

3. Numerical analyses

To explore the effects of climate risk scenarios, specifically the influence of a stochastic transition process, the reinforcing dependence between this transition and insurer claims, and the implications of brown and green investing, we carry out a numerical analysis with realistically calibrated data. Our methodology involves executing a Monte Carlo simulation using 2 million random pathways, ensuring consistency by using the same set of random numbers. When simulating random numbers from copulas, see Equation (9), we employ the "copula" R-package developed by Hofert *et al.* (2024).

3.1 Input parameters

The parameters for our simulation are detailed in Table 1. The coefficient of variation c_v has been calculated based on realistic parameters of a medium-sized German non-life insurer estimated in Eling *et al.* (2009) (see Equation (2)). The expected rate of return μ_r is derived from inflation-adjusted net return rates of all German primary non-life insurers during the period 2001–2021 (BaFin, 2023; World Bank, 2023). Net return rate, in this context, refers to the yield earned by insurers on their investment portfolios after deducting expenses and charges. The standard deviation of the overall portfolio σ_r is estimated using the net return rate (unadjusted for inflation) and the capital market line, as described by Eckert and Gatzert (2018), which is calibrated for annual risk-return profiles without incorporating inflation considerations. The standard deviation of the return rate of the subportfolios is calculated according to Equation (8). Premium loading δ is chosen for illustration purposes, see Equation (3). The full transition shocks (FTS) for brown and other assets according to Equation (6) are based on quantitative results of 2022 IORP Stress test, where FTS^{Brown} is calculated as the average shock for investments in the five sectors mining, coke and petroleum, non-metallic mineral, electricity and gas, and land transport (EIOPA, 2022d). The full transition shock for green assets FTS^{Green} was estimated based on the assumption that green stocks and bonds would each experience an approximate increase of 20–30% and 5–10%, respectively, in the event of an immediate transition, as precise and reliable data are not available due to the lack of sufficient standardization of such investments (see Equation (6)). The proportion of brown assets is based on estimations of Weyzig *et al.* (2014). The proportion of green assets is calculated by taking the difference between climate-policy-relevant investments made by pension funds, as defined by Battiston *et al.* (2017), and the proportion of brown assets, see

Table 1. Input parameters

Parameter	Notation	Value
Initial equity	E_0	18.63 million €
Time horizon	n_0, N	$n_0 = 2021$, $N = 2050$
Exponential regression function for expected claims	$\mu_n = a \cdot b^n$	$a = 6.344\text{e}{-11}$, $b = 1.014$
Coefficient of variation of claims	$c_v = \frac{\sigma_n}{\mu_n}$	5.64%
Expected rate of return	μ_r	2.99%
Standard deviation of return rate of the overall portfolio	σ_r	7.12%
Standard deviation of return rate of subportfolios	σ	7.36%
Premium loading for insurer (portion of standard deviation)	δ	0.5
Transition shock factor for brown investments	FTS^{Brown}	24.1%
Transition shock factor for green assets	FTS^{Green}	15.0%
Transition shock factor for other assets	FTS^{Other}	12.5%
Proportion of brown investments in assets	q^{Brown}	4%
Proportion of green investments in assets	q^{Green}	4.3%
Correlation between green and brown assets	$\rho_{Brown,Green}$	0.43
Correlation between green and other assets	$\rho_{Green,Other}$	0.62
Correlation between brown and other assets	$\rho_{Brown,Other}$	0.57
Dependence describing copula for annual transition progress and annual claims	C^{St}_{θ}	C^{St}_{2}

Source(s): Author's own work

Equation (5). We further investigate the proportions of brown and green investments in Section 3.2. The pairwise correlations between the three subportfolios, see Equation (7), were estimated using the daily price returns of the S&P Oil and Gas Exploration and Production Select Industry Index (brown), S&P Global Clean Energy Index (green) and S&P 500 (other) from October 2013 to 2023 as representatives of their respective asset classes (S&P, 2023a, b, c). The parameter θ of dependence describing copula is chosen for illustration purposes, see Equation (9). The model's sensitivity to the copula parameter is explored in Section 3.3. The initial equity is calibrated to achieve a one-year default probability of 0.5% in the base case (see Table 2), as required as a minimum by Solvency II.

3.2 Results

In this section, we will begin by examining the influence of climate risk scenarios on the finite-time default probability and the expected surplus according to Equation (11) and (12) across various time horizons leading up to 2050. Our scenarios are comparable to the climate scenarios according to NGFS (2022) in the following way. Our baseline scenario without a transition process corresponds to the "Hot House World" scenario according to NGFS (2022), where global climate policies are not implemented sufficiently to effectively stop global warming or also the "No Additional Action" scenario according to Bank of England (2022), where no further climate policies are introduced and thus transition risks are neglected. The scenarios featuring a Rayleigh-distributed transition process align with the "Orderly Transition" scenarios as per NGFS (2022) or the "Early Action" scenarios according to Bank of England (2022). In these scenarios, climate protection measures are immediately implemented and intensify at a relatively gradual pace throughout the scenario horizon, aiming for net-zero greenhouse gas emissions by 2050. A Pareto-distributed transition process implicitly addresses the risk of a "Disorderly Transition" (NGFS, 2022) or a "Late Action" (Bank of England, 2022) through its distribution structure, making significant transition steps especially likely in the upcoming decade. The case with an exponentially distributed transition offers a middle ground between the two aforementioned scenarios.

Table 2. Impact of climate risk scenarios on expected surplus (12) and finite-time default probability (11), considering the distribution of transition process (4) and reinforcing dependence allowance (9)

Resulting key figures Scenario (Distribution of transition process)	Expected Surplus in million €		Finite-Time Default Probability in %	
		Change to Base in %		Change to Base in %
2022				
Base (no transition)	24.5		0.50	
Rayleigh	24.0	–2.0	0.58	+16
Exponential	24.0	–2.0	0.58	+16
Pareto	24.1	–1.6	0.60	+20
Rayleigh + Reinforcing Dep.	24.0	–2.0	0.63	+26
Exponential + Reinforcing Dep.	24.0	–2.0	0.72	+44
Pareto + Reinforcing Dep.	24.1	–1.6	0.86	+72
2025				
Base (no transition)	43.6		2.84	
Rayleigh	41.5	–4.8	3.42	+20
Exponential	41.5	–4.8	3.45	+21
Pareto	41.7	–4.4	3.45	+21
Rayleigh + Reinforcing Dep.	41.5	–4.8	3.66	+29
Exponential + Reinforcing Dep.	41.5	–4.8	3.92	+38
Pareto + Reinforcing Dep.	41.7	–4.4	4.15	+46
2030				
Base (no transition)	81.2		4.22	
Rayleigh	75.4	–7.1	5.26	+25
Exponential	75.4	–7.1	5.29	+25
Pareto	75.8	–6.7	5.28	+25
Rayleigh + Reinforcing Dep.	75.4	–7.1	5.58	+32
Exponential + Reinforcing Dep.	75.4	–7.1	5.93	+41
Pareto + Reinforcing Dep.	75.7	–6.8	6.19	+47
2040				
Base (no transition)	182.2		4.70	
Rayleigh	164.1	–9.9	6.01	+28
Exponential	164.1	–9.9	6.05	+29
Pareto	165.0	–9.4	6.02	+28
Rayleigh + Reinforcing Dep.	164.0	–10.0	6.37	+36
Exponential + Reinforcing Dep.	163.9	–10.0	6.75	+44
Pareto + Reinforcing Dep.	164.9	–9.5	7.02	+49
2050				
Base (no transition)	328.6		4.76	
Rayleigh	288.5	–12.2	6.14	+29
Exponential	288.4	–12.2	6.17	+30
Pareto	287.8	–12.4	6.14	+29
Rayleigh + Reinforcing Dep.	288.1	–12.3	6.50	+37
Exponential + Reinforcing Dep.	288.7	–12.4	6.89	+45
Pareto + Reinforcing Dep.	287.0	–12.7	7.16	+50

Source(s): Author’s own work

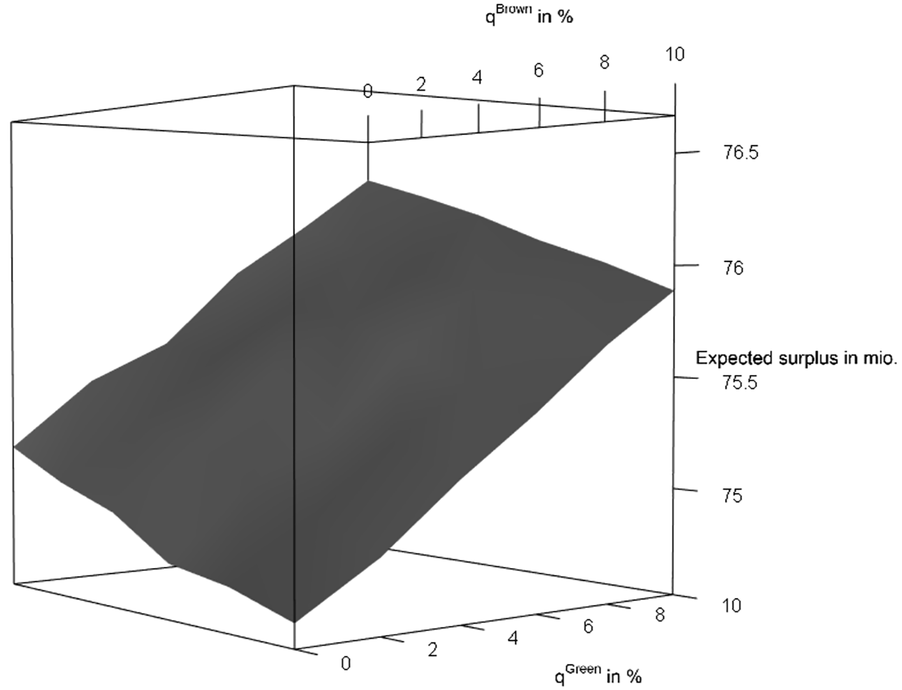
The simulation results are displayed in Table 2. Here, we can observe the key metrics for different distributions of the stochastic transition process according to Equation (4), and whether or not a dependence, as explained in Equation (9), is permitted. Initially, we observe that the impact of the climate risk scenarios on the ruin probability is more pronounced than on the expected surplus. This can be attributed to the definition of ruin probability as a tail measure. Differences in surplus across the scenarios are only marginal, with slight variations in the case of Pareto-distributed transition due to its slightly lower mean average transition step per year, as depicted in Figure 2. However, the question of whether the transition is considered as a stochastic transition process at all is of significant importance for the surplus. We observe a decrease in the expected profit by 2.0% over a one-year horizon and up to a 12.7% reduction by

2050. Allowing for a reinforcing dependence between transition and claims has minimal influence on the expected surplus, since dependencies do not affect the mean of a distribution, but in our context, they significantly influence the tail behavior of it.

In our examination of the finite-time ruin probability over a one-year time horizon, we find that this probability with a transition process following a Rayleigh distribution is lower than that of an exponential distribution. This ruin probability for exponential distribution, in turn, is lower than that of a Pareto distribution. This observed sequence can be mainly attributed to the increased likelihood of significant transition steps and the variance differences, as illustrated in Figure 3. When we disregard reinforcing dependence, the distinctions between these distributions are slight and tend to diminish for time horizons extending beyond 2030. However, when reinforcing dependence is factored in, the differences in ruin probabilities become more pronounced across all distributions. When reinforcing dependence is considered, the ruin probabilities increase by 26% for the Rayleigh distribution and up to 72% for the Pareto distribution over a one-year horizon. In contrast, excluding this dependence results in a 16–20% increase in ruin probability for Rayleigh and Pareto distributions, respectively. Specifically, accounting for a transition results in a rise in ruin probability ranging from 16% in 2022 to 29% by 2050. Looking towards the time horizon up to 2050 with reinforcing dependence, the growth in ruin probabilities lies between 37% for the Rayleigh distribution and 50% for the Pareto distribution. In summary, within this model framework, incorporating a stochastic transition process (following a Pareto distribution) along with a reinforcing dependence between transition progress and annual claims can increase the ruin probability by an estimated 46–72%.

Another key focus of this paper is the influence of portfolio composition, specifically the proportion of brown and green investments according to Equation (5), on both the finite-time ruin probability and the expected surplus. For this analysis, we consider the time horizon of 2030, where diversification effects are excluded by adjusting the standard deviation of the subportfolios, see Equation (8). As we can see in Table 2 for the time horizon up to 2030, the seven scenarios under consideration differ with respect to the expected surplus mainly in whether a transition is included or not. The inclusion of reinforcing dependence or the choice of distribution for the transition process has no or only minimal effect on this metric. Therefore, in the following sensitivity analysis, we focus on the scenario with a Rayleigh-distributed transition process and without reinforcing dependence. Further investigations of the other scenarios have shown barely measurable differences in the subsequent sensitivity analysis. As expected, Figure 5 shows that the expected surplus is higher the smaller the proportion of brown investments q^{Brown} and the larger the proportion of green investments q^{Green}, which do experience a positive shock from the transition process. The growth rate appears to follow a linear trend, see Figure 5. With a green proportion of 0%, decreasing the brown proportion from 10% to 0% increases the expected profit by 0.72%. In contrast, by fixing the proportion of brown investments at 0% and increasing the green proportion from 0% to 10%, the expected profit increases by 1.74%. In this context, we can conclude that, in terms of expected profit, increasing investments in green assets seems to be more effective than divesting from brown assets.

In our examination of the ruin probability, we primarily focus on transitions distributed according to Rayleigh and Pareto, as the values derived from the exponential distribution consistently lie between those of the Rayleigh and Pareto distributions in terms of ruin probability. Table 3 clearly illustrates that, in the absence of reinforcing dependence, a decrease in brown investments (from 10% to 0%) leads to a reduction in the ruin probability of 2.3–2.4%. This contrasts with the reduction in ruin probability resulting from a corresponding increase (from 0% to 10%) in green investments, which ranges from 4.7 to 5.2%. However, when reinforcing dependence is incorporated, the dynamics change. The effect of elevating green investments from 0% to 10% increases by 20–50%, specifically from 4.7% to 5.7% and from 5.2% to 7.8%. Conversely, the influence of brown investments intensifies more



Source(s): Author’s own work

Figure 5. Expected surplus by 2030 for different portfolio compositions (q^{Brown}, q^{Green}) ranging from 0% to 10%, with a Rayleigh-distributed transition process without reinforcing dependence

substantially. With the consideration of reinforcing dependence, the impact of augmenting brown investments rises by 39% (for Rayleigh) to 67% (for Pareto). This differentiation emphasizes the importance of accounting for dependencies when evaluating the effects of investment decisions on ruin probabilities. Whether dependence is included or excluded can significantly alter the perceived efficacy of green versus brown investment strategies.

Table 3. Finite-time default probability (11) by 2030, considering various portfolio compositions (5) and scenarios

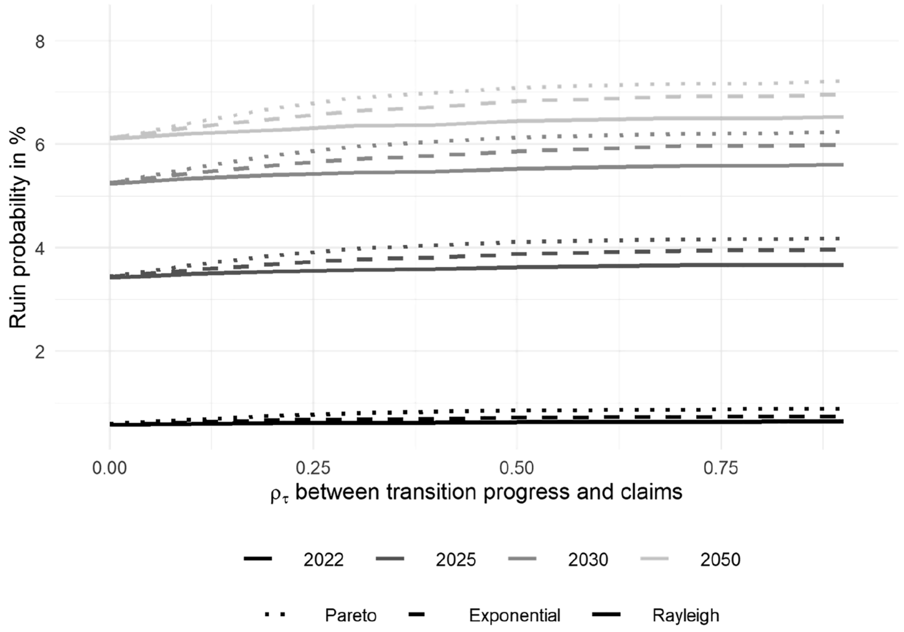
Portfolio composition	Scenario Rayleigh (change to the first composition)	Pareto (change to the first composition)	Rayleigh + Reinforcing dep. (change to the first composition)	Pareto + Reinforcing dep. (change to the first composition)
$q^{Brown} = 0\%$, $q^{Green} = 0\%$	5.31%	5.34%	5.60%	6.26%
$q^{Brown} = 10\%$, $q^{Green} = 0\%$	5.43% (+2.3%)	5.47% (+2.4%)	5.78% (+3.2%)	6.51% (+4.0%)
$q^{Brown} = 0\%$, $q^{Green} = 10\%$	5.06% (−4.7%)	5.06% (−5.2%)	5.28% (−5.7%)	5.77% (−7.8%)
$q^{Brown} = 10\%$, $q^{Green} = 10\%$	5.14% (−3.2%)	5.15% (−3.6%)	5.43% (−3.0%)	5.99% (−4.3%)

Source(s): Author’s own work

3.3 Sensitivity analysis

In the final section of the numerical analysis, we aim to explore the model's sensitivity, focusing first on the ruin probability in relation to the strength of the dependence, expressed in terms of Kendall's tau according to Equation (10), of the dependence describing copula defined in Equation (9). For this purpose, we examine various time horizons to understand how the ruin probability behaves under various applicable scenarios (Rayleigh + Reinforcing Dep., Exponential + Reinforcing Dep. and Pareto + Reinforcing Dep.). In Figure 6, it is evident that when the transition process follows a Pareto distribution, the ruin probability is more sensitive to changes in the strength of dependence compared to when it is exponentially distributed. Furthermore, the sensitivity of the ruin probability for the exponentially distributed transition process is higher than that for a Rayleigh-distributed process. These characteristics are consistent across all time horizons. While the sensitivity of the probability of ruin with an exponentially distributed transition process is still relatively low over a one-year horizon and close to that of the Rayleigh distribution, this sensitivity of the exponential distribution intensifies more with an increasing horizon than the sensitivity of the Rayleigh-distributed one. We also observe that the sensitivity increases with the length of the time horizon, but beyond 2030, the changes become marginal, see Table 2. This underscores the uncertainty arising from the transition for the ruin probability of non-life insurers in the coming decade.

As the final point in the model's sensitivity analysis, we consider the immediacy of the reinforcing dependency. As already noted in Section 2.3, the reinforcing dependence between physical and transition risks within the same year is at least questionable. Political responses to natural disasters, strategic shifts in climate policy and the resulting market reactions often take longer than a year to unfold with customer preferences requiring even more time to adjust. Therefore, we perform the same scenario analysis as in Section 3.2 (see Table 2), but this time assuming that the transition progress in year *n* depends on the claims from the previous year *n*



Source(s): Author's own work

Figure 6. Ruin probability across different time horizons and strengths of dependencies between annual transition progress and claims

− *1*, as described in Section 2.3, rather than on the claims from the same year *n*. Thus, in this model, the insurance claims in the first year 2022 are stochastically independent of the transition progress in 2022, and the transition progress in 2023 now depends on the claims from the previous year 2022.

The minimal deviations between the values in Table 4 and those in Table 2, observed without reinforcing dependence, are due to the stochastic nature of the model, despite using 2 million random pathways. In Table 4, we observe three key differences compared to Table 2. First, changing the immediacy of the dependencies has little to no impact on the expected profit. Second, for the time horizon of 2022, there is barely any difference between the scenarios with and without reinforcing dependence, as the dependency only takes effect in the following year. Lastly, the impact of reinforcing dependence on the finite-time ruin probability is significantly weaker when a one-year delay is assumed. For example, the difference compared to the corresponding transition scenarios without reinforcing dependence is only 3–9% higher in 2025, 4–9% in 2030 and 4–10% in both 2040 and 2050. In comparison, the differences in the case of immediacy were 9–25% in 2025, 7–22% in 2030 and 8–21% in both 2040 and 2050 (see Table 2). These results demonstrate how critical the immediacy of market reactions to physical risks from climate change is for financial stability.

4. Summary

In this article, we examine the impact of both physical and transitional climate risks on the balance sheet of non-life insurers, addressing a research gap in the comprehensive understanding of these interconnected risks. To model physical risks, we employ a straightforward extrapolation combined with an assumption of a constant coefficient of variation, addressing factors like more severe and frequent natural disasters and thus increasing expected claims. In the next step, we model the impact of transition risks by introducing a stochastic transition process aiming to evaluate progress towards limiting global warming to 2°C until 2050. This transition process is further integrated within the risk framework specific to a non-life insurer, where the impact is dependent on the proportion of brown and green investments. Beyond the pure accumulation of both transition and physical risk effects, our study connects these models, introducing a copula-based reinforcing dependence between transition risks and claims arising from physical risks, assuming high transition risks are more likely associated with high physical risks.

Our scenario analyses show that the risk of a disorderly transition is particularly influential in shaping the risk landscape for non-life insurers. Shorter time horizons already reveal a substantial impact on the ruin probability, whereas the repercussions on profit accentuate as the time frame extends. The influence of the reinforcing dependence between physical and transition risks primarily affects the probability of ruin, and does so considerably. Specifically, when considering a Pareto-distributed transition process with reinforcing dependencies, we observe an increase in the probability of ruin from 50% in 2050 to 72% in 2022. Interestingly, the direction and magnitude of the influence from investment strategies, whether the investments lean towards green or brown assets, depend on the consideration of the dependence between physical and transition risks. The sensitivity analysis also indicates that some scenarios become more sensitive to the strength of the reinforcing dependence compared to others as the time horizon extends. However, within this model framework, no significant change in sensitivity occurs after 2030. In addition, we observe that a delayed dependence of one year has a significantly lower impact on the probability of ruin.

This model offers valuable insights for non-life insurers, serving as both a practical guide and a catalyst for further research in climate finance. Insurers must revise their risk models to account for both the increasing frequency and severity of extreme weather events and the shifting regulatory environment driven by climate change mitigation efforts. This includes enhancing climate risk assessment and embedding climate-related financial risks into capital allocation and pricing strategies. For policymakers, these findings underscore

Table 4. Impact of climate risk scenarios on expected surplus (12) and finite-time default probability (11), considering the distribution of transition process (4) and reinforcing dependence allowance with a time lag of one year (9)

Resulting key figures **Scenario (Distribution of transition process)**	**Expected Surplus in million €**	Change to Base in %	**Finite-Time Default Probability in %**	Change to Base in %
2022				
Base (no transition)	24.5		0.51	
Rayleigh	24.1	–1.6	0.58	+14
Exponential	24.1	–1.6	0.58	+14
Pareto	24.1	–1.6	0.60	+18
Rayleigh + Reinforcing Dep.	24.0	–2.0	0.57	+12
Exponential + Reinforcing Dep.	24.0	–2.0	0.58	+14
Pareto + Reinforcing Dep.	24.1	–1.6	0.59	+16
2025				
Base (no transition)	43.7		2.86	
Rayleigh	41.6	–4.8	3.43	+20
Exponential	41.6	–4.8	3.45	+21
Pareto	41.8	–4.3	3.46	+21
Rayleigh + Reinforcing Dep.	41.6	–4.8	3.53	+23
Exponential + Reinforcing Dep.	41.6	–4.8	3.63	+27
Pareto + Reinforcing Dep.	41.8	–4.3	3.71	+30
2030				
Base (no transition)	81.2		4.22	
Rayleigh	75.5	–7.0	5.25	+24
Exponential	75.5	–7.0	5.28	+25
Pareto	75.8	–6.7	5.28	+25
Rayleigh + Reinforcing Dep.	75.5	–7.0	5.41	+28
Exponential + Reinforcing Dep.	75.6	–6.9	5.57	+32
Pareto + Reinforcing Dep.	76.0	–6.4	5.66	+34
2040				
Base (no transition)	182.3		4.69	
Rayleigh	164.2	–9.9	6.01	+28
Exponential	164.2	–9.9	6.03	+29
Pareto	165.2	–9.4	6.02	+28
Rayleigh + Reinforcing Dep.	164.4	–9.8	6.17	+32
Exponential + Reinforcing Dep.	164.5	–9.8	6.36	+36
Pareto + Reinforcing Dep.	165.4	–9.3	6.45	+38
2050				
Base (no transition)	328.9		4.75	
Rayleigh	288.7	–12.2	6.13	+29
Exponential	288.6	–12.3	6.16	+30
Pareto	288.0	–12.4	6.14	+29
Rayleigh + Reinforcing Dep.	288.7	–12.2	6.30	+33
Exponential + Reinforcing Dep.	288.6	–12.3	6.49	+37
Pareto + Reinforcing Dep.	288.0	–12.4	6.58	+39

Source(s): Author's own work

the urgent need for stronger regulations that not only mandate more transparent climate risk disclosures but also provide insurers with clearer frameworks for managing these evolving risks and their reinforcing dependencies. Strengthening regulatory structures to encompass both physical and transition climate risks is essential for maintaining financial stability and resilience within the insurance sector. Additionally, future research should focus on refining these models, particularly regarding the treatment of assets and liabilities, and improving data accuracy around the nature of the transition process and the dependencies within. As Carney (2015) appropriately notes, "By managing what gets measured, we can break the tragedy of the horizon."

Notes

1. In the context of climate change “stranded assets” denote investments that lose value prematurely due to shifts towards a lower-carbon economy, driven by regulatory changes, technological advancements, and evolving market preferences.
2. https://ec.europa.eu/eurostat/documents/3859598/5902521/KS-RA-07-015-EN.PDF
3. A sensitivity analysis addressing the extent of the impact of a one-year lag on the non-life insurer is conducted in Section 3.3.

References

Alessi, L., Ossola, E. and Panzica, R. (2021), “What greenium matters in the stock market? The role of greenhouse gasemissions and environmental disclosures”, *Journal of Financial Stability*, Vol. 54, 100869, doi: 10.1016/j.jfs.2021.100869.

Ardia, D., Bluteau, K., Boudt, K. and Inghelbrecht, K. (2023), “Climate change concerns and the performance of green versus Brown stocks”, *Management Science*, Vol. 69 No. 12, pp. 7607-7632, doi: 10.1287/mnsc.2022.4636.

Bank of England (2022), “Results of the 2021 climate biennial exploratory scenario (CBES)”, available at: https://www.bankofengland.co.uk/stress-testing/2022/results-of-the-2021-climate-biennial-exploratory-scenario (accessed 7 July 2023).

Battiston, S. and Monasterolo, I. (2021), “On the dependence of investor’s probability of default on climate transition scenarios”, Working Paper, available at: https://ssrn.com/abstract=3743647

Battiston, S., Mandel, A., Monasterolo, I., Schütze, F. and Visentin, G. (2017), “A climate stress-test of the financial system”, *Nature Climate Change*, Vol. 7 No. 4, pp. 283-288, doi: 10.1038/nclimate3255.

Ben Ammar, S., Braun, A. and Eling, M. (2015), *Alternative Risk Transfer and Insurance-Linked Securities: Trends, Challenges and New Market Opportunities*, I.VW HSG Schriftenreihe (56), Verlag Institut für Versicherungswirtschaft der Universität St. Gallen, St. Gallen.

Bolton, P. and Kacperczyk, M.T. (2023), “Global pricing of carbon-transition risk”, *Journal of Finance*, Vol. 78 No. 6, pp. 3677-3754, doi: 10.1111/jofi.13272.

Bua, G., Kapp, D., Ramella, F. and Rognone, L. (2022), “Transition versus physical climate risk pricing in European financial markets: a text-based approach”, ECB Working Paper No. 2677, available at: https://ssrn.com/abstract=3860234

Bundesanstalt für Finanzdienstleistungsaufsicht (BaFin) (2019), “Merkblatt zum Umgang mit Nachhaltigkeitsrisiken”, available at: https://www.bafin.de/SharedDocs/Downloads/DE/Merkblatt/dl_mb_Nachhaltigkeitsrisiken.html (accessed 30 January 2023).

Bundesanstalt für Finanzdienstleistungsaufsicht (BaFin) (2023), “Statistik der BaFin – Erstversicherungsunternehmen”, available at: https://www.bafin.de/DE/PublikationenDaten/Sta-tistiken/Erstversicherung/erstversicherung_node.html (accessed 27 September 2023).

Burnecki, K., Kukla, G. and Weron, R. (2000), “Property insurance loss distributions”, *Physica A: Statistical Mechanics and its Applications*, Vol. 287 Nos 1-2, pp. 269-278, doi: 10.1016/S0378-4371(00)00453-2.

Campiglio, E., Daumas, L., Monnin, P. and von Jagov, A. (2023), “Climate-related risks in financial assets”, *Journal of Economic Surveys*, Vol. 37 No. 3, pp. 950-992, doi: 10.1111/joes.12525.

Carney, M. (2015), “Breaking the tragedy of the horizon – climate change and financial stability”, available at: https://www.bankofengland.co.uk/-/media/boe/files/speech/2015/breaking-the-tragedy-of-the-horizon-climate-change-and-financial-stability.pdf?la=en&hash=7C67E785651862457D99511147C7424FF5EA0C1A (accessed 13 September 2024).

Clayton, D. (1978), "A model for association in bivariate life tables and its application in epidemiological studies of familial tendency in chronic disease incidence", *Biometrica*, Vol. 65 No. 1, pp. 141-151, doi: 10.1093/biomet/65.1.141.

Climate Analytics (2024), "Climate impact explorer – annual expected damage from river floods", available at: https://climate-impact-explorer.climateanalytics.org/ (accessed 3 November 2024).

Dasgupta, S., van Maanen, N., Gosling, S.N., Piontek, F., Otto, C. and Schleussner, C.-F. (2021), "Effects of climate change on combined labour productivity and supply: an empirical, multi-model study", *The Lancet – Planetary Health*, Vol. 5 No. 7, pp. E455-E465, doi: 10.1016/S2542-5196(21)00170-4.

Desnos, B., Le Guenedal, T., Morais, P. and Roncalli, T. (2023), "From climate stress testing to climate value-at-risk: a stochastic approach", Working Paper, available at: https://ssrn.com/abstract=4497124

Dionne, G. and Desjardins, D. (2022), "A Re-examination of the U.S. Insurance market's capacity to pay catastrophe losses", Effects of Climate Risks on Non-Life Insurers' Resilience - First Report (SCOR-Project), Vol. 25 No. 4, pp. 515-549, doi: 10.1111/rmir.12228, available at: https://foundation.scor.com/sites/default/files/2022-05/ClimatRisk_22-05-11_paper%2Bonline%20appendix.pdf (accessed 13 September 2024).

Eckert, J. and Gatzert, N. (2018), "Risk- and value-based management for non-life insurers under solvency constraints", *European Journal of Operational Research*, Vol. 266 No. 2, pp. 761-774, doi: 10.1016/j.ejor.2017.10.030.

Eling, M., Gatzert, N. and Schmeiser, H. (2009), "Minimum standards for investment performance: a new perspective on non-life insurer solvency", *Insurance: Mathematics and Economics*, Vol. 45 No. 1, pp. 113-122, doi: 10.1016/j.insmatheco.2009.05.003.

European Central Bank (ECB) (2021), "Climate-related risk and financial stability", ECB/ESRB Project Team on climate risk monitoring, available at: https://www.ecb.europa.eu/pub/pdf/other/ecb.climateriskfinancialstability202107~87822fae81.en.pdf (accessed 17 April 2023).

European Insurance and Occupational Pensions Authority (EIOPA) (2021), "Report on non-life underwriting and pricing in light of climate change", EIOPA-BoS-21/25.

European Insurance and Occupational Pensions Authority (EIOPA) (2022a), "Application guidance on rrunning climate change materiality assessment and using climate change scenarios in the ORSA", EIOPA-BoS-22/329.

European Insurance and Occupational Pensions Authority (EIOPA) (2022b), "Methodological principles of insurance stress testing – climate change component", EIOPA-BOS-21/579.

European Insurance and Occupational Pensions Authority (EIOPA) (2022c), "2022 IORP stress test", EIOPA-22-310.

European Insurance and Occupational Pensions Authority (EIOPA) (2022d), "Report on 2022 IORP climate stress test", EIOPA-BoS-22/551.

European Insurance and Occupational Pensions Authority (EIOPA) (2022e), "European insurers' exposure to physical climate change risk", EIOPA-22/278.

European Insurance and Occupational Pensions Authority (EIOPA) (2022f), "Prudential treatment of sustainability risks", Discussion Paper, EIOPA-BoS-22-527.

European Insurance and Occupational Pensions Authority (EIOPA) (2023), "Impact underwriting – report on the implementation of climate-related adaption measures in non-life underwriting practices", EIOPA-BoS-22-593.

Gatzert, N. and Özdil, O. (2024), "The impact of dependencies between climate risks on the asset and liability side of non-life insurers", *European Actuarial Journal*, Vol. 14, pp. 1-19, doi: 10.1007/s13385-023-00364-2.

Gaudemet, J.-B., Deschamps, J. and Vinciguerra, O. (2022), "A stochastic climate model – an approach to calibrate the climate-extended risk model (CERM)", Working Paper, doi: 10.48550/arXiv.2205.02581.

Gesamtverband der Deutschen Versicherungswirtschaft (GDV) (2023), “Klimawandelszenarien im ORSA – Ansätze zur Umsetzung der aufsichtsrechtlichen Anforderungen”, available at: https://www.gdv.de/resource/blob/86344/46ffde1f286355d5e34502611c042148/klimawandelszenarien-im-orsa-download-data.pdf (accessed 7 January 2023).

Gillingham, K. and Stock, J.H. (2018), “The cost of reducing greenhouse gas emissions”, *Journal of Economic Perspectives*, Vol. 32 No. 4, pp. 53-72, doi: 10.1257/jep.32.4.53.

Hofert, M., Kojadinovic, I., Maechler, M. and Yan, J. (2024), “Package ‘copula’ - multivariate dependence modeling with copulas”, available at: https://cran.r-project.org/web/packages/copula/copula.pdf (accessed 20 March 2024).

In, S.Y., Park, K.Y. and Monk, A. (2019), “Is ‘being green’ rewarded in the market?: an empirical investigation of carbon emission intensity and stock returns”, Stanford Global Project Center Working Paper, available at: https://ssrn.com/abstract=3020304

International Actuarial Association (IAA), Intergovernmental Panel on Climate Change Working Group I (IPCC WGI) (2022), “Climate science: a summary for actuaries”, Joint IPCC WGI and IAA Paper, available at: https://www.actuaries.org/IAA/Documents/Publications/Papers/Climate_Science_Summary_Actuaries.pdf (accessed 7 April 2023).

Lamond, J. and Penning-Roswell, E. (2014), “The robustness of flood insurance regimes given changing risk resulting from climate change”, *Climate Risk Management*, Vol. 2, pp. 1-10, doi: 10.1016/j.crm.2014.03.001.

Lehtonen, T.-K. (2017), “Objectifying climate change: weather-related catastrophes as risks and opportunities for reinsurance”, *Political Theory*, Vol. 45 No. 1, pp. 32-51, doi: 10.1177/0090591716680684.

Lucas, C.H. and Booth, K.I. (2020), “Privatizing climate adaptation: how insurance weakens solidaristic and collective disaster recovery”, *WIREs Climate Change*, Vol. 11 No. 6, pp. 1-14, doi: 10.1002/wcc.676.

Milkau, U. (2022), “Climate change risk: demands and expectations imposed on banks”, *Journal of Risk Management in Financial Institutions*, Vol. 15 No. 3, pp. 278-300, doi: 10.69554/avbw8233.

Network for Greening the Financial System (NGFS) (2022), “NGFS scenarios for central banks and supervisors”, available at: https://www.ngfs.net/sites/default/files/medias/documents/ngfs_climate_scenarios_for_central_banks_and_supervisors_.pdf.pdf (accessed 24 August 2022).

Network for Greening the Financial System (NGFS) (2024), “NGFS phase 4 scenario explorer – emissions | CO2 (total)”, available at: https://data.ene.iiasa.ac.at/ngfs (accessed 3 December 2024).

Nordhaus, W. (2011), “The economics of tail events with an application to climate change”, *Review of Environmental Economics and Policy*, Vol. 5 No. 2, pp. 240-257, doi: 10.1093/reep/rer004.

Nordhaus, W. (2018), “Projections and uncertainties about climate change in an era of minimal climate policies”, *American Economic Journal: Economic Policy*, Vol. 10 No. 3, pp. 333-360, doi: 10.1257/pol.20170046.

Oh, S.S., Sen, I. and Tenekedijeva, A.-M. (2022), “Pricing of climate risk insurance: regulation and cross-subsidies”, Finance and Economics Discussion Series 2022-064, available at: https://www.federalreserve.gov/econres/feds/files/2022064pap.pdf (accessed 9 May 2023).

Parry, M.L., Canziani, O.F., Palutikof, J.P., van der Linden, P.J. and Hanson, C.E. (2007), “Climate change 2007: impacts, adaptation and vulnerability”, Contribution of Working Group II to the Fourth Assessment Report of the Intergovernmental Panel on Climate Change, Cambridge, UK.

Pástor, Ľ., Stambaugh, R.F. and Taylor, L.A. (2021), “Sustainable investing in equilibrium”, *Journal of Financial Economics*, Vol. 142 No. 2, pp. 550-571, doi: 10.1016/j.jfineco.2020.12.011.

Ravina, A. and Hentati-Kaffel, R. (2020), “The impact of low-carbon policy on stock returns”, *Working Paper*, available at: https://dx.doi.org/10.2139/ssrn.3444168

Roncoroni, A., Battison, S., Escobar-Farfán, L.O.L. and Martinez-Jaramillo, S. (2021), “Climate risk and financial stability in the network of banks and investment funds”, *Journal of Financial Stability*, Vol. 54, 100870, doi: 10.1016/j.jfs.2021.100870.

Standard and Poors (S&P) (2023a), “S&P Dow Jones indices - S&P 500”, available at: https://www.spglobal.com/spdji/en/indices/equity/sp-500/ (accessed 17 October 2023).

Standard and Poors (S&P) (2023b), “S&P Dow Jones indices - S&P global clean”, *Energy Index*, available at: https://www.spglobal.com/spdji/en/indices/esg/sp-global-clean-energy-index/ (accessed 17 October 2023).

Standard and Poors (S&P) (2023c), “S&P Dow Jones indices - S&P oil and gas exploration and production select industry index”, available at: https://www.spglobal.com/spdji/en/indices/equity/sp-oil-gas-exploration-production-select-industry-index/ (accessed 17 October 2023).

Swiss Re (2023), “Sigma explorer”, available at: https://sigma-explorer.com/ (accessed 20 July 2023).

Swiss Re (2024), “New record of 142 natural catastrophes accumulates to USD 108 billion insured losses in 2023, finds Swiss Re institute”, available at: https://www.swissre.com/press-release/New-record-of-142-natural-catastrophes-accumulates-to-USD-108-billion-insured-losses-in-2023-finds-Swiss-Re-Institute/a2512914-6d3a-492e-a190-aac37feca15b (accessed 24 September 2024).

Task Force on Climate-related Financial Disclosures (TCFD) (2017), “Technical supplement: the use of scenario analysis in disclosure of climate-related risks and opportunities”, available at: https://assets.bbhub.io/company/sites/60/2021/03/FINAL-TCFD-Technical-Supplement-062917.pdf (accessed 21 November 2022).

Tesselaar, M., Botzen, W.J.W. and Aerts, J.C.J.H. (2020), “Impacts of climate change and remote natural catastrophes on EU flood insurance markets: an analysis of soft and hard reinsurance markets for flood coverage”, *Atmosphere*, Vol. 11 No. 2, p. 146, doi: 10.3390/atmos11020146.

University of Cambridge Institute for Sustainability Leadership (CISL) (2015), “Unhedgeable risk: how climate change sentiment impacts investment”, Cambridge, UK.

Vermeulen, R., Schets, E., Lohuis, M., Kölbl, B., Jansen, D.-J. and Heering, W. (2018), “An energy transition risk stress test for the financial system of the Netherlands”, De Nederlandsche Bank Occasional Studies, Vol. 16 No. 7.

Weitzmann, M.L. (2009), “On modeling and interpreting the economics of catastrophic climate change”, *The Review of Economics and Statistics*, Vol. 91 No. 1, pp. 1-19, doi: 10.1162/rest.91.1.1.

Weyzig, F., Kuepper, B., van Gelder, J.W. and van Tilburg, R. (2014), “The price of doing too little too late”, Green European Foundation - Green New Deal Series, 11.

World Bank (2023), “Indicators – inflation, consumer prices”, available at: https://data.worldbank.org/indicator/FP.CPI.TOTL.ZG?view=chart (accessed 22 August 2023).

Zhao, Z.-J., Chen, X.-T., Liu, C.-Y., Yang, F., Tan, X., Zhao, Y., Huang, H., Wei, C., Shi, X.-L., Zhai, W., Guo, F. and van Ruijven, B.J. (2020), “Global climate damage in 2 °C and 1.5 °C scenarios based on BCC_SESM model in IAM framework”, *Advances in Climate Change Research*, Vol. 11 No. 3, pp. 261-272, doi: 10.1016/j.accre.2020.09.008.

Corresponding author
Onur Özdil can be contacted at: onur.oezdil@fau.de