The Impact of Climate Change on Systemic Risk: A Top-Down Assessment of Transition Risk in the Eurozone

Mira Mareike Funder

Dissertation written under the supervision of Professor Filippo De Marco

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Abstract

This thesis analyzes the effect of transition risk from climate change on systemic risk in the financial sector in the Eurozone by estimating the expected capital shortfall of 237 publicly listed financial institutions in the Eurozone, conditional on a climate stress scenario, focusing on trends and concentration patterns. The capital shortfall is estimated utilizing a market-based top-down climate stress test methodology introduced by Jung et al. (2023), by first estimating time-varying Climate Betas for each financial institution through a rolling regression of the company stock returns on the returns of a Stranded Asset Portfolio, which is constructed to serve as a proxy for transition risk. Next, the variable CRISK is estimated, representing the expected capital shortfall of each financial institution under a stress scenario, represented by 50% decline in the return of the Stranded Asset Portfolio over a six-month period. The advantage of this methodology is that it estimates climate risk dynamically, and thus addresses its time-varying nature. Furthermore, it requires only publicly available data and relies on minimal assumptions (Jung et al., 2023). The findings of the analysis in this research thesis reveal a positive aggregate average CRISK of EUR 594,39 billion for the data sample, with differences in the distribution of CRISK among countries, sub-industries and individual financial institutions, and a significant upward trend in aggregate CRISK values throughout the observation period. In addition, the mean aggregate marginal CRISK, representing the difference in CRISK compared with a non-stressed scenario, is EUR 40,42 billion.

Keywords: *Climate Change, Eurozone, Financial Stability, Stranded Assets, Stress Testing, Systemic Risk, Top-Down Stress Test, Transition Risk*

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Resumo

Este estudo trata do impacto do risco de transição decorrente do risco sistémico do sector financeiro na Zona do euro, onde é estimado um défice de capital esperado de 237 instituições financeiras cotadas na Zona do euro, condicionado a um cenário de estresse climático, com foco nas tendências e nos padrões de concentração. O défice de capital é estimado utilizando uma metodologia de teste de estresse climático top-down baseada no mercado, introduzida por Jung et al. (2023), estimando primeiro os Betas Climáticos variáveis no tempo para cada instituição financeira através de uma regressão contínua dos retornos das acções da empresa sobre os retornos de uma Carteira de Activos Desconhecidos, que é construída para servir de proxy para o risco de transição. Em seguida, é estimada a variável CRISK, que representa o défice de capital esperado de cada instituição financeira num cenário de stress, representado por uma descida de 50% no retorno da carteira de activos não recuperáveis durante um período de seis meses. A vantagem desta metodologia é a previsão do risco climático de forma dinâmica, abordando assim a sua natureza variável no tempo. Além disso, requer apenas dados publicamente disponíveis e baseia-se em pressupostos mínimos (Jung et al., 2023).

Os resultados da análise revelam um CRISK médio agregado positivo de 594,39 mil milhões de euros para a amostra de dados. Além disso, a CRISK marginal média agregada, que representa a diferença na CRISK em comparação com um cenário sem stress, é de 40,42 mil milhões de euros.

Palavras-chave: *Activos irrecuperáveis, Alterações climáticas, Estabilidade financeira, Riscos de transição, Risco sistémico, Testes de esforço, Teste de esforço top-down, Zona Euro*

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List of Abbreviations

AR	Abnormal Return
$BCBS$	Basel Committee on Banking Supervision
CAR	Cumulative Abnormal Return
$CF_{Str,t}$	Stranded Asset Portfolio
CO_2	Carbon Dioxide
COP	UN Climate Change Conference
$COVID$-19	Coronavirus Disease 2019
$CRISK$	Capital Shortfall under Climate Stress Scenario
D_{it}	Book Value of Debt
DMG	Share of total losses from natural disasters relative to GDP
EBA	European Banking Authority
ECB	European Central Bank
E_{it}	Market Value of Equity
EMU	European Monetary Union
ESG	Environmental, Social, Governance
ETF	Exchange Traded Funds
EU	European Union
EUR	Euros
FSL_t	Stranded Asset Index
GDP	Gross Domestic Product
GHG	Greenhouse Gases
$GICS$	Global Industry Classification Standard
IMF	International Monetary Fund
$IPCC$	Intergovernmental Panel on Climate Change
$MCRISK$	Marginal CRISK
MKT_t	Market Portfolio
MV	Market Capitalization
$NGFS$	Network for Greening the Financial System
OLS	Ordinary Least Squares
USD	US Dollar
$\beta_{it}^{Climate}$	Climate Beta
θ	Climate Stress Scenario
$°C$	Degree Celsius
$\Sigma CRISK$	Aggregate CRISK
$\Sigma MCRISK$	Aggregate MCRISK
ΣMV	Aggregate Market Capitalization

1. Introduction

Climate change is one of the most significant risks of this century. The Intergovernmental Panel on Climate Change (IPCC) finds that climate change has led to an increasing severity and prevalence of extreme events that cause adverse effects on the ecosystem and the global population (IPCC, 2022). If global warming reaches 1,5 °C in the near future, the severity of climate hazards will further accelerate, increasing its risk to the population and nature (IPCC, 2022). Further, several studies highlight the negative economic impacts of global warming, leading to global GDP losses of 7-23% by 2100[1] in the absence of climate change policies (Burke et al., 2015; Kahn et al., 2019; Kalkuhl & Wenz, 2020).

However, climate change not only negatively impacts the environment, the population, and the economy but also poses systemic risks to the financial sector through the following transmission channel: Climate change leads to *physical risks* and *transition risks* for companies.

Physical risks result from direct damages to physical assets caused by disruptions due to climate change (Battiston et al., 2021). If companies fail to fully mitigate their exposure to physical risks from climate change or insure against them, this can lead to companies incurring high costs from the effects of physical risk and, as a result, at worst, being unable to meet their debt obligations (Campiglio et al., 2018). This, in turn, affects the loan default rate and profitability of the lending financial institutions (Battiston et al., 2021). In cases where financial institutions suffer significant financial losses due to climate risks, this could reduce their ability to provide credit, creating liquidity risk. If regulators do not impose adequate limits to financial institutions' exposures to climate risk, this can create a systemic risk to the financial sector (Cambridge Institute for Sustainability Leadership (CISL), 2019).

However, high economic costs can arise not only from physical risk but also from *transition risks,* resulting from shifting climate policies implemented to support the transition to a low-carbon economy (Cambridge Institute for Sustainability Leadership (CISL), 2019). Although these transitions benefit human welfare in the long run, disruptive structural adjustments can jeopardize financial stability through transition risks, creating systemic risk (Campiglio et al., 2018). Thus, the required climate policy measures, such as GHG mitigation measures, are a new challenge for financial regulators (Reinders et al., 2023). One critical question for regulators is what impact climate change and the transition towards an environmentally friendly

[1] compared to 2015

economy will have on the liquidity and profitability of financial institutions and, thus, on financial stability (Campiglio et al., 2018).

The objective of this research thesis is to analyze the impact of transition risk on systemic risk in the Eurozone by answering the following research question:

Research Question: *How does climate-related transition risk impact financial institutions and systemic risk within the Eurozone, and what are the dynamic trends and concentration patterns associated with climate-related risks?*

To answer this research question, the empirical study in this thesis applies a market-based top-down methodology for climate stress testing introduced by Jung et al. (2023), analyzing the effect of climate transition risk on systemic risk by estimating the expected capital shortfall of publicly listed financial institutions in the Eurozone conditional on a climate stress scenario.
The expected capital shortfall is estimated as follows: First, a *Stranded Asset Portfolio* is constructed to model transition risk. Based on this proxy, time-varying *Climate Betas* $\beta_{it}^{Climate}$ of the observed financial institutions are estimated through a rolling regression of the company returns on the returns of the Stranded Asset Portfolio $CF_{Str,t}$, representing the sensitivity of company returns to returns of $CF_{Str,t}$. Next, *CRISK*, representing the expected capital shortfall of a financial institution under a climate stress scenario, is estimated. CRISK is a function of each financial institution's market value of equity E_{it}, book value of debt D_{it}, total capital ratio *k,* Climate Betas $\beta_{it}^{Climate}$, and a climate stress scenario θ. The analyzed *climate stress scenario* θ is a 50% decline in the return of the Stranded Asset Portfolio over a six-month period. To analyze the systemic risk to the financial sector in the Eurozone, $\Sigma CRISK$, representing the aggregate CRISK of all financial institutions, is calculated. $\Sigma CRISK$ can be interpreted as the amount of capital required to offset the undercapitalization of the financial system in a stress scenario. To isolate the impact of climate stress on the expected shortfall, marginal CRISK is further estimated, representing the difference of CRISK compared to the expected capital shortfall in a non-stressed scenario (Jung et al. 2023).
Additionally, a sensitivity analysis is performed, estimating CRISK based on alternative climate stress scenarios.
The advantages of this methodology by Jung et al. (2023) are that it estimates climate risk dynamically and thus addresses its time-varying nature. By assessing the effect of climate risk on asset prices, this market-based stress test can identify the exposure of financial institutions

to effects of climate change which may only materialize in the future but have the potential to drive a bank into bankruptcy within a brief period, given that their asset prices fall today in response to negative news about the distant future. Further, the model only requires publicly available data and relies on minimal assumptions.

Jung et al. (2023) applied this methodology to a data sample consisting of banks located in the United States, United Kingdom, Canada, Japan, and France over a period from 2000 to 2021. However, this methodology or a similar market-based top-down stress test focusing on the effect of transition risk on financial institutions within the Eurozone has not yet been published to my knowledge.

Thus, this research thesis aims to fill this research gap by analyzing the magnitude and distribution of CRISK in the Eurozone, analyzing 237 publicly listed financial institutions over an observation period from 2003 to 2022.

The findings of the analysis in this research thesis reveal a positive average $\Sigma CRISK$ of EUR 594,39 billion for the data sample, with heterogeneities in the distribution of CRISK between countries within the Eurozone as well as between different sub-industries and individual financial institutions. Moreover, a significant upward trend in $\Sigma CRISK$ values throughout the observed period is identified. In addition, the mean aggregate marginal CRISK value has a statistically significant positive mean value of EUR 40,42 billion across the entire dataset, extending to each country. This implies that the defined climate stress scenario increases the expected aggregate capital shortfall of the analyzed financial institutions.

The remaining sections of the thesis are structured as follows: Chapter 2 provides a literature review outlining the theoretical foundations of the climate stress testing and the research questions analyzed in this thesis. Chapter 3 presents the data set and the methodology applied. The empirical results of the analysis are presented in Chapter 4. The discussion in Chapter 5 provides answers to the research questions, limitations of the analysis and suggestions for further research. Finally, Chapter 6 provides a conclusion.

2. Literature Review

This literature review is divided in three sections: First, a theoretical background of climate change and climate-related risks for financial institutions is presented. Subsequently, the purpose and methods of climate stress testing, as well as climate stress test results in academic literature examining the impact of climate change on financial stability are reviewed. Finally, the research questions analyzed in this research thesis are presented.

2.1. Theoretical Background

2.1.1. Climate Change

Climate change refers to *"long-term shifts in temperatures and weather patterns"* (United Nations, 2023, para.1). Although such shifts can also be caused by natural processes, the 2023 IPCC report on climate change concludes that human activities, mainly through the emission of GHG, have caused global warming, resulting in an estimated total global temperature increase 1,09°C between 1850-1900 and 2010-2019 (IPCC, 2023a).

Present impacts of climate change

The 2023 IPCC report on climate change emphasizes the extensive environmental and social consequences of climate change (IPCC, 2023), which has caused the destruction of ecosystems, stimulated migration and climate-related diseases, and reduced food security. Today, between 3,3 and 3,6 billion people live in areas that are severely threatened climate change, exposing millions to food and water insecurity and a significantly higher mortality rate because of extreme weather events (IPCC, 2023). Beyond these vulnerable regions, Europe is also exposed to the effects of climate change, with an increase of average temperatures by more than twice the global average between 1991 and 2021, at an average rate of about 0,5°C per decade (World Meteorological Organization (WMO), 2022).

However, the European region is one of the most advanced regions regarding climate change adaptation and mitigation. For example, GHG emissions in the European Union were lowered by 31% between 1990 and 2020 (World Meteorological Organization, 2022), while global GHG emissions increased by 39% over the same period (Statista, 2023b). In addition, the European Union has adopted several policies to mitigate and adapt to the impacts of climate change, such as the European Green Deal, which was adopted in 2021 with the objective to achieve climate neutrality in all EU countries by 2050 (European Commission, 2021).

To mitigate the adverse effects of climate change on a global scale, the Paris Agreement was adopted by 196 countries at the UN Climate Change Conference (COP21) in 2015, marking a historic treaty with the target of limiting global warming to below 2°C (UNFCCC, 2023).

In addition to the direct effects on human livelihoods, climate change also causes economic damage to sectors exposed to climate change (IPCC, 2023). Fossil fuel sectors such as oil and gas are particularly susceptible to shifts in demand, which could fall by 35% by 2030 compared to 2020 (Eceiza et al., 2020).

An analysis of the long-term impacts of climate change by Kahn et al. (2019) on GDP per capita further shows that an annual temperature increase of 0,04°C is projected to reduce global real GDP per capita by 7,22% by 2100. However, if the Paris Agreement target of limiting temperature rise to 0,01°C per year is met, this GDP loss could be reduced to 1,07% (Kahn et al., 2019).

In the European Union, climate change has caused an estimated EUR 560 billion in costs between 1980 and 2021, of which EUR 56,6 billion were incurred in 2021 alone, with an increasing trend (European Environment Agency, 2023; Eurostat, 2022).

Climate Change Scenarios

Climate change scenarios have been developed to estimate future global GHG emission pathways and their impact on climate change, providing policymakers with advice on the risks of climate change. Further, these scenarios are an integral input for assessing the financial risks of climate change. The scenarios are based on various assumptions, such as population growth, resource consumption, and technological progress (IPCC, 2000; NGFS, 2020).

To enhance comparability in climate change analyses, the scientific community generally uses a standard set of climate change scenarios, first defined and published by the IPCC in 1990 (IPCC, 2000).

In addition, the Network for Greening the Financial System (NGFS) has published a set of reference scenarios that are suitable for climate stress testing purposes, taking into account physical and transition risks (NGFS, 2020).

2.1.2. Climate Risks

Climate-related risks for companies originate from two distinct sources: The direct consequences of climate change itself, referred to as *physical risk*, and the impacts resulting from responses to climate change, referred to as *transition risk*.

The extent to which individual companies are affected by these risks depends on their level of exposure, vulnerability, and adaptability to these factors (Caldecott et al., 2021).
In addition, the interactions between the drivers of climate risk and the risks themselves can amplify or mitigate overall climate risk. While several climate assessments acknowledge the existence of these complex climate risks, a cohesive and coherent framework for evaluating these risks has not yet been developed (Simpson et al., 2021).
Further, there are differences in exposure to climate risk across countries and sectors, determined by different factors such as geological factors, but also political, economic, and financial systems (Basel Committee on Banking Supervision, 2021b).
This section provides an overview of physical and transition risks, their categorization, drivers, and potential financial implications for companies.

Physical Risks

Physical risks arise from direct damages to physical assets caused by disruptions due to climate change, resulting in potential costs or financial losses (Battiston et al., 2021). Physical risks are projected to increase significantly by 2050, with severe global consequences (Cambridge Institute for Sustainability Leadership (CISL), 2019).
Physical risks can be classified as *acute or chronic* (TCFD, 2017): *Acute risk* refers to the risks posed by specific events, such as the increased frequency and severity of natural disasters and extreme weather events due to climate change (Basel Committee on Banking Supervision, 2021a). In contrast, *chronic risks* result from long-term shifts in climate patterns, including changes in temperature, precipitation, sea level, and biodiversity loss (Despres et al., 2021).
Moreover, physical risks can have both *direct* and *indirect impacts*. While the *direct impacts* of climate change may initially be confined to a specific location, their *indirect impacts* can extend across sectors, value chains, and national borders (Cambridge Institute for Sustainability Leadership (CISL), 2019).

Companies can face significant *financial consequences* due to physical risks: On the one hand, acute physical risk presents specific threats to companies' physical assets, in particular, infrastructure and real estate assets (Cambridge Institute for Sustainability Leadership (CISL), 2019). On the other hand, chronic physical risk can diminish overall productivity, affecting labor and capital productivity (International Labour Office, 2019).

Transition Risks

The transition to a low-carbon economy gives rise to *transition risks,* for example stemming from changing climate policies (Cambridge Institute for Sustainability Leadership (CISL), 2019). Although this transition presents new opportunities, can also disrupt business activities (Battiston et al., 2021).

The drivers of transition risks can be categorized into several risk types:

1. *Climate policy risks:* Resulting from unanticipated, time-inconsistent, or non-credible regulations and policies aimed at mitigating the negative impacts of climate change or at improving adaptation to climate change, which may lead to a decline in equity of exposed companies (TCFD, 2017). Policy measures that aim to reduce GHG emissions, such as carbon pricing mechanisms, are examples of climate policy risks (Basel Committee on Banking Supervision, 2021b; Daumas, 2023).
2. *Legal Risks:* Due to newly implemented climate-related policies, companies may be exposed to legal compliance risks arising from climate change litigation if they do not adapt to these policies or comply with disclosure requirements (TCFD, 2017).
3. *Technology Risk:* The emergence of new technologies to support the transition to a low-carbon economy may change supply and demand dynamics, affecting companies' competitiveness, profitability, and costs (TCFD, 2017).
4. *Market Risk:* Shifts in supply and demand patterns due to climate change can affect product and service markets (TCFD, 2017). These changes may result from shifts in consumer sentiment driven by increased awareness of and demand for climate-friendly products and services. This increased consumer awareness may also increase reputational risk (Basel Committee on Banking Supervision, 2021b). In addition, market risk can arise from changes in investor sentiment driven by incorporating climate risk implications into investment decisions (Basel Committee on Banking Supervision, 2021b). For example, Alessi et al. (2021) demonstrated that ceteris paribus, investors in the European stock market tend to accept lower returns in order to hold more environmentally friendly and transparent assets given the credibility of the transition to a low-carbon economy.

Financial Impact of Physical and Transition Risk

The financial impact of both physical and transition risks is manifested in the company's financial statements as follows (TCFD, 2017):

On the *income statement*, the effects are twofold: Firstly, climate-related risks can lead to reduced revenues due to lower demand and factor productivity. Secondly, companies may incur increased expenses to mitigate the negative consequences of climate risks (TCFD, 2017).
Furthermore, the impacts extend to *cash flows*, which tend to be lower and exhibit greater volatility in the presence of climate-related risks (Huang et al., 2018).
On the *balance sheet*, impacts may arise from damages from acute and chronic physical risks, leading to accelerated asset depreciation (TCFD, 2017). In addition, the transition to a low-carbon economy may result in the emergence of *stranded assets* (Semieniuk et al., 2022). In terms of corporate capital structure, companies may require increased leverage to account for reduced cash flows. Huang et al. (2018) find that climate risk is associated with an increase in long-term debt and a decrease in short-term debt. Furthermore, the ability to raise new debt in the face of increased exposure to climate risk may be affected.

These adverse effects can reduce financial performance. In a study analyzing the effect of climate risk on firm performance in 55 countries between 1993 and 2012, Huang et al. (2018) find that increased climate risk has a significant negative relationship with return on assets and cash flow from operations and a positive relationship with earnings volatility.

<u>*Stranded Assets*</u>

Stranded Assets are assets that lose or significantly depreciate in their economic value before their expected useful life, are underutilized, or cannot generate as much revenue as expected because of the transition to a lower carbon economy, resulting in financial losses (Daumas, 2023; Matikainen, 2022).
Companies in carbon-intensive industries face particular challenges caused by transition risks, as changes in climate policies can cause assets, such as fossil fuel reserves, power plants, and infrastructure, to become stranded (Eren et al., 2022). However, assets can also become stranded due to physical influences, such as assets in the agriculture sector that become unusable because the soil becomes barren (Caldecott et al., 2021).
To limit global warming to 1,5 °C in line with the Paris Agreement, 60% of oil and gas reserves and 90% of coal reserves must be left unused (Welsby et al., 2021). Moreover, the lifespan of coal-fired power plants would be reduced by 10 to 30 years to meet the targets (Fofrich et al., 2020).

2.1.3. *Transmission of Climate Risk to Financial Instability*

According to a survey of 861 financial professionals, academics, regulators, and economists, climate change is considered the most relevant risk to financial markets over the next three decades (Stroebel & Wurgler, 2021). Further, financial supervisors recognize its systemic implications, causing risk to financial stability (Basel Committee on Banking Supervision, 2021a; Daumas, 2023; Despres et al., 2021).

This section explains the transmission channels through which climate risks can affect financial institutions and, ultimately, financial stability.

Transmission Channels

The BCBS classifies the exposure of financial institutions to climate risks into microeconomic and macroeconomic transmission channels, stemming from both physical and transition risk drivers (Basel Committee on Banking Supervision, 2021b).

Microeconomic Transmission Channel

The *microeconomic transmission channel* describes how climate risk drivers affect the entities in which financial institutions invest or provide credit, thereby creating climate-related financial risk within the financial systems (Basel Committee on Banking Supervision, 2021b).

Since financial institutions have limited physical assets and thus minimal Scope 1 or 2 GHG emissions, their climate risk exposure arises primarily from Scope 3 emissions associated with the financed emissions of the companies in their investment and debt portfolios (Partnership for Carbon Accounting Financials (PCAF), 2022).[2]

In scenarios where climate risks negatively impact these portfolio companies, and their mitigation measures prove insufficient, in addition to not being insured against the risks, the potential for financial losses arises (Campiglio et al., 2018). Notably, only about 35% of climate-related losses were insured in the European Union in 2020 (Despres et al., 2021). In cases where losses within portfolio companies are significant, this can lead to companies defaulting on their debt, which subsequently affects the loan default rate and the profitability of the lending financial institutions (Battiston et al., 2021).

If a significant proportion of debt defaults, financial institutions may be constrained in providing capital to other firms, creating liquidity risk. Further, they may face a higher probability of default because of the increased risk faced by the borrower (Cambridge Institute for Sustainability Leadership (CISL), 2019).

[2] A definition of Scope 1-3 GHG emissions is available in the appendix in Section 8.1.1.

If regulators do not implement sufficient limits on financial institutions' exposure to climate risks and if these institutions further neglect independent risk management, climate risk can thus affect the financial position of financial institutions and in turn affect financial stability (Basel Committee on Banking Supervision, 2021b).

Macroeconomic Transmission Channel

The *macroeconomic transmission channel* explains how climate risk drivers can affect macroeconomic elements such as total factor productivity, GDP growth, inflation, and interest rates, and thus, the economies in which banks operate (Basel Committee on Banking Supervision, 2021b).

The BCBS concludes that the impact of climate risk drivers is reflected in conventional financial risk categories[3] and does not require the introduction of a new risk classification (Basel Committee on Banking Supervision, 2021b).

Implications for Financial Stability

The ECB identifies climate change as a source of systemic risk with implications for financial markets and financial institutions (Emambakhsh et al., 2022).

Regarding transition risks, the main concern for financial stability is the consequence of climate policies that are inconsistent over time, lack credibility, and are unanticipated. These policies could lead to a significant decline in the equity values of exposed companies, which would also affect investors in these firms (Battiston et al., 2021; Daumas, 2023).

In terms of physical risks, the interconnectedness of these risks may contribute to increased climate-related risks. This, in turn, has the potential to trigger a systemic amplification of risks to financial stability (Battiston et al., 2021) and also lead to a sudden repricing of assets, resulting in the potential liquidation of securities exposed to physical risk, leading to a fire-sale dynamic (Emambakhsh et al., 2022).

In addition, physical risk can amplify transition risk, as there may be a sudden change in climate policy in response to a natural disaster, for example (Daumas, 2023).

The ECB's Financial Stability Review shows that there is climate-related concentration risk in the Eurozone and that greater exposure to carbon-intensive companies is associated with higher expected losses for banks. Around 35% of these expected losses across the Eurozone come from the 10% most sensitive banks to carbon price fluctuations (Emambakhsh et al., 2022). Although corporate GHG emissions have decreased between 2018 and 2021, the exposure of

[3] i.e. credit risk, market risk, operational risk, liquidity risk, and reputational risk

Eurozone banks to carbon-intensive companies has not decreased significantly (Emambakhsh et al., 2022).
Regarding GHG emissions, vulnerability is concentrated across and within sectors (Hiebert, 2021). For example, 70% of the credit risk exposure to physical risk in the banking system of the European Union is concentrated in just 25 banks (Despres et al., 2021).
Moreover, the exposure of Eurozone banks to climate policy-relevant sectors amounts to EUR 1,9 trillion in 2020, representing about 52% of the Eurozone non-financial corporate loan portfolio (Despres et al., 2021).

2.1.4. Pricing of Climate Risk in Financial Markets

Although research suggests that climate risks are priced into financial markets, concerns remain as to whether current prices fully reflect these risks (Eren et al., 2022).
For example, in a survey of 861 financial professionals and academics, a significant majority indicated that current asset prices underestimate climate risks. In addition, challenges in correctly modelling climate risks arise from the inherent uncertainty associated with climate risks (Stroebel & Wurgler, 2021).
Concerning physical risks, there is mixed evidence as to whether they are correctly priced in credit and equity markets. Regarding transition risk, there is evidence that it is priced into financial markets, but uncertainty remains about the extent to which this pricing truly captures transition risk (Eren et al., 2022).
Bolton & Kacperczyk (2021) find that within *equity markets*, stocks of carbon-intensive firms earn higher returns, controlling for a wide range of return predictors, suggesting that investors demand a premium for carbon exposure. Furthermore, Barnett (2023) finds that market expectations of new climate policies reduce companies' share prices in the fossil fuel sector. In *fixed-income markets*, there is evidence that companies with larger GHG emissions and lower ESG scores carry a higher credit risk[4] (Eren et al., 2022).

2.1.5. Climate Risk Mitigation by Financial Supervisors in the Eurozone

To mitigate the negative impacts of climate change, several climate policies, such as the European Climate Law, have been adopted in the Eurozone (European Council, 2023).
However, concerning the financial system, the negative impacts of climate change on financial stability require systemic risk mitigation by financial supervisors (Battiston et al., 2021).

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[4] in terms of bond yield spreads and distance to default

The monetary policy measures implemented by the ECB aim to mitigate climate change and its associated risks and promote the transition to a more environmentally friendly financial system (European Central Bank, 2023b).

The *ECB Climate Agenda* comprises several measures to achieve these objectives, including:

1. Incorporating climate change in monetary policy activities, such as corporate sector asset purchases (European Central Bank, 2022b,)
2. Strengthening and expanding the assessment and management of financial risks in banks from climate change in the context of the ECB's role as supervisor of European banks under the Single Supervisory Mechanism (European Central Bank, 2023a). To achieve these objectives, regular climate stress tests of the financial system are planned starting in 2023 (European Central Bank, 2023d). In addition, the ECB maintains an ongoing monitoring of physical and transition risks faced by financial institutions (Emambakhsh et al., 2022).

2.2. Climate Stress Tests

Central banks and financial supervisors are increasingly urging financial institutions to assess and manage their financial risks associated with climate change and have begun to develop climate stress tests to assess the financial system's vulnerability to climate change's impacts (Battiston et al., 2021). As of January 2023, more than 60 climate stress tests were planned or completed worldwide (Walther, 2023).

This chapter first defines stress tests, then introduces the general structure of stress tests, and discusses climate-specific stress tests.

2.2.1. Definition of Stress Testing

Stress testing is a quantitative simulation method mainly applied by financial regulators to assess the solvency and, thus, the resilience of financial institutions to risks arising from an extreme but realistic financial or macroeconomic shock scenario (Baudino et al., 2018; Casellina et al., 2020; Chan-Lau, 2013).

Another purpose of stress testing is to provide the public with information on the stability of the aggregate banking sector to establish or increase public confidence in the resilience of financial institutions in a stress scenario (Chan-Lau, 2013; Daniëls et al., 2017; Farmer et al., 2022).

The first Eurozone-wide stress test of the financial system was conducted by the Committee of European Banking Supervisors (CEBS)[5] in 2009 (Xoual, 2013). Today, central banks regularly conduct stress tests to assess the financial system's resilience to a range of macroeconomic and financial shock scenarios (Acharya et al., 2023).

In the Eurozone, the ECB conducts annual EU-wide stress tests, including thematic stress tests such as the Climate Risk Stress Test in 2022 or the Liquidity Risk Sensitivity Analysis in 2019 (European Central Bank, 2023e).

2.2.2. Stress Test Construction

There are several considerations when developing stress tests as part of the risk management of financial institutions, which are presented in this section in the order of the stress test's construction.

Purpose and Scope

Stress testing may be conducted for both macroprudential and microprudential purposes (Farmer et al., 2022). *Microprudential stress testing* assesses the resilience of financial institutions, focusing on institution-specific vulnerabilities. In contrast, *macroprudential stress testing* assesses the robustness of the entire financial system to shocks, ensuring that systematically relevant financial institutions can function as reliable providers of credit under stress scenarios.

In practice, macroprudential and microprudential stress tests are often combined, especially in concentrated markets with several systemically important financial institutions (Daniëls et al., 2017).

The scope of a stress test may include only individual financial institutions or the entire financial system. Although stress tests primarily target banks, other financial institutions should also be included as non-bank assets grow in the financial system (Farmer et al., 2022).

Selection of Stress Scenarios and Risk Factors

Next, a suitable stress scenario is developed. Stress scenarios for stress tests should be *"severe but plausible"* (Farmer et al., 2022, p. 14) shocks that are expected to adversely impact the analyzed sample of financial institutions.

When constructing stress scenarios, a distinction can be made between *hypothetical and historical cases*.

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[5] Today, the CEBS has become the European Banking Authority (EBA)

Regarding the *selection of risk factors to be stressed*, many stress tests focus on macroeconomic or financial shocks, but this may neglect other risks, such as climate risk, to which financial institutions may be exposed (Farmer et al., 2022).

A stress scenario also considers the *magnitude of the shocks*, the transmission channels, the *length* of the scenario, and the *intervals* over which shocks are measured (Acharya et al., 2023) Climate stress tests usually comprise a period of up to 30 years (Walther, 2023), as demonstrated by the ECB's economy-wide climate stress test (Alogoskoufis et al., 2021). Regarding climate stress tests, the reference climate change scenarios published by the NGFS are widely used by financial supervisors (European Central Bank, 2022c; NGFS, 2020).

Methodology

The next step is defining a stress testing model that translates the shock scenario to financial variables (Reinders et al., 2023b). The methodologies for stress testing can be classified into bottom-up and top-down stress testing.

In a *bottom-up stress test*, the assessed financial institution usually calculates its risk exposure based on a specific methodology and under supervision (Baudino et al., 2018; Daniëls et al., 2017). This methodology allows the stress test to be based on granular, internal firm data. However, in practice, it can be difficult and time-consuming to collect data from financial institutions in a standardized way, which may make it difficult to respond to new shock scenarios (Daniëls et al., 2017).

A *top-down stress test* is carried out by a public authority based on a pre-defined stress test framework. The procedure of a top-down stress test is as follows: First, hypothetical macroeconomic stress scenarios affecting the banking system in a specified geographical area are constructed (Chan-Lau, 2013). Next, the impact of the selected stress scenario is estimated by the responsible central bank (Daniëls et al., 2017). An advantage of the top-down stress testing methodology is that the testing process can be performed more quickly than with bottom-up tests, allowing a swift response to new shock scenarios. However, a challenge is to model the analyzed risks correctly, as it requires sufficiently granular data (Daniëls et al., 2017).

As part of the *Financial Sector Assessment Programme (FSAP)*, top-down stress tests have been incorporated by the IMF and the World Bank since 1999 (Chan-Lau, 2013).

One specific type of top-down stress testing is *market-based top-down stress testing*. Market-based top-down stress tests assume that climate risks are priced into equity markets, which is suggested by several studies, as discussed in Section 2.1.3. This method uses market perceptions to assess the stability of banks, as banks can be affected by self-fulfilling bank runs based on market perceptions. An advantage of this method is that it requires less data input compared to other methods (Chan-Lau, 2013).

Top-down and bottom-up stress tests, ceteris paribus, do not have to produce the same results as each test is based on different data, but are expected to produce similar results (Daniëls et al., 2017). An alternative methodology is the *hybrid approach*, which combines the bottom-up and top-down methodologies. This approach has, for example, been implemented in the 2023 EU-wide stress test performed by the EBA (European Banking Authority, 2023).

Outcome and Determination of Passing Criteria

The final step is to establish a decision rule defining the criteria by which the stress test results can be considered passed (Farmer et al., 2022).

2.2.3. Application of Stress Testing Framework on Climate Stress Testing

The stress testing framework presented in the previous section can be applied to various financial and macroeconomic stress scenarios, including climate stress scenarios. This section describes how stress testing methods can be applied to climate stress testing and provides examples of studies that have applied these different methods.

Methods

Both microprudential and macroprudential stress tests can be conducted in the context of climate stress tests.

Furthermore, climate stress scenarios for climate stress tests can be based on transition risk or physical risk, including chronic or acute risk (Reinders et al., 2023b). Often, the stress test scenarios by NGFS or IPCC are applied, usually covering a more extended period, to reflect the long-term nature of climate risk (Walther, 2023).

Climate stress tests can be conducted employing a *bottom-up stress test methodology* (e.g., Faiella et al., 2022; Mandel et al., 2021) or a *top-down stress test methodology* (e.g., Jung et al., 2023; H. J. Reinders et al., 2023; Schober et al., 2021; Vermeulen et al., 2018).

In addition, four approaches to modeling climate stress tests can be distinguished (Reinders et al., 2023b):

1. The *micro-financial approach* converts climate shocks into microeconomic variables at the level of individual companies or assets, such as earnings and company value. These variables are then translated into financial risks for the analyzed financial institutions (e.g., Reinders et al., 2023).

2. The *macro-financial approach* translates climate shock variables into macroeconomic indicators such as GDP or inflation. An empirical estimation of the relationship between macroeconomic and financial variables, such as credit default rates, is then carried out (e.g., Allen et al., 2020; Vermeulen et al., 2018)
3. The *non-structural approach* treats economic variables as black boxes and directly estimates the relationship between climate shocks and financial variables (e.g., Battiston et al., 2017; Jung et al., 2023).
4. Finally, the *disaster risk approach* connects the results of disaster risk models, often used in insurance companies, to their potential impact on the financial sector.

A further distinction can be made between static, dynamic, and network-based climate stress tests (Daumas, 2023):

1. *Static stress tests* measure the direct impact of a shock on the observed firms (e.g., Faiella et al., 2022). A problem with this method is that short-term stress tests reduce transition risk to a one-off negative shock, whereas transition risk is likely to be a long-term phenomenon (Daumas, 2023).
2. In contrast to static stress tests, *dynamic stress tests* add a macroeconomic scenario and also take into account, for example, feedback loops from the financial sector to the real economy (e.g., Vermeulen et al., 2018).
3. Furthermore, *network stress tests* additionally evaluate the amplification potential within the financial system by analyzing second-round effects, such as fire sales (e.g., Battiston et al., 2017).

2.2.4. Climate Stress Test Results in Literature

This section presents the findings of a range of studies that applied different climate stress testing frameworks.

Focusing on *physical risk*, Mandel et al. (2021) employ a bottom-up stress network-based test to analyze the global effect of flood risk on financial stability. They authors find that exposure to systemic risk depends on countries' exposure to physical risk and leverage, and that the adverse effects of physical risks can be amplified by financial interconnectedness (Mandel et al., 2021).

Furthermore, a number of studies have highlighted the vulnerability of financial stability to *transition risks*, which can lead to systemic risks:
For example, Faiella et al. (2022) estimated the impact a carbon tax on Italian household income and corporate profits utilizing a bottom-up approach analyzing survey data and energy prices. The study finds that for households, even a significant carbon tax of EUR 800/ton CO_2, which would increase the share of vulnerable households to 11,8%, would not increase the share of vulnerable households to the level of the sovereign debt crisis. In contrast, introducing a EUR 50/ton CO_2 carbon tax on businesses would increase the share of vulnerable businesses to 45,0% compared to a baseline scenario of 22,4% vulnerable businesses. In comparison, an EUR 800/ton CO_2 carbon tax would increase the share of vulnerable businesses to 91,6%. A limitation of this study is that it is based on a short-term scenario and is static (Faiella et al., 2022).
Similarly, Reinders et al. (2023a) applied a micro-financial top-down methodology, applying a Merton contingent claims model to estimate the effect of a carbon tax shock on the value of corporate debt in the Dutch banking sector and found that the market value of bank assets could fall by 9-32% of the CET1 capital of the Dutch banking system in a EUR 200/ton CO_2 carbon tax shock scenario (Reinders et al., 2023a).

Further, focusing on *GHG reduction policies*, a study by Schober et al. (2021) focuses on the impact of the transition risk of an unexpected climate policy that increases GHG reduction targets in the German financial system. Based on the NiGEM macroeconometric model that is applied in NGFS scenarios, the authors differentiate between sectors according to their emission intensity and find medium losses in individual financial sectors as well as in the entire German financial system (Schober et al., 2021).
Another study focusing on the impact of climate policies was conducted by Battiston et al. (2017). In a network-based climate stress test of large Eurozone banks, the authors estimate values at risk as a result of changing climate policies, utilizing a non-structural approach, and find that the timing and expectations of new climate policies matter: An early and stable framework of GHG-reducing policies that is anticipated by the market would allow for gradual adjustments in asset values, while a late and sudden framework could lead to systemic risk (Battiston et al., 2017).
Further, Vermeulen et al. (2018) focused on top-down macro-financial stress tests, assessing the impact of energy transition risks on Dutch financial institutions by applying four *"severe but plausible energy transition scenarios"* (Vermeulen et al., 2018, p.12) to assets held by

Dutch financial institutions. Depending on the scenario, the authors find that financial institutions' assets could decline by between 3 and 11 % (Vermeulen et al., 2018).

Finally, Jung et al. (2023) applied a *top-down, market-based, non-structural stress test* to measure the impact of transition risks on the expected capital shortfall of financial institutions in multiple countries. The authors introduced the variable CRISK, which estimates *"the expected capital shortfall [...] under a climate stress scenario"* (Jung et al., 2023, pp. 2–3) of financial institutions to assess whether they have sufficient capital reserves to withstand losses resulting from transition risk stress. The authors find a significant increase in CRISK across observed banks during the fossil fuel collapse in 2020, reaching an aggregate value of almost 2 trillion USD (Jung et al., 2023).

Climate Stress Tests by the European Central Bank

In the EU, climate stress tests are part of the thematic stress tests and are planned to be conducted annually (European Central Bank, 2023e). The ECB works closely with the EBA, part of the European Supervisory Authorities (ESA), to conduct stress tests (European Central Bank, 2023c).

While until 2020, stress tests mainly focused on transition risk, more recent stress tests incorporate both physical and transition risks. Further, there is a trend towards longer horizons for scenario analysis of up to 30 years and incorporating more granular data, such as sector-level GHG intensity (Despres et al., 2021).

Examples of recent ECB stress tests include a bottom-up climate risk stress test for 104 Single Supervisory Mechanism (SSM) banks in 2022 (European Central Bank, 2022a) and a top-down economy-wide climate stress test for 1300 Eurozone banks in 2021 (Alogoskoufis et al., 2021).

2.2.5. Current Challenges and Limitations of Climate Stress Tests

There are multiple challenges and limitations to conducting climate change stress tests. Climate risks are characterized by a high degree of complexity and uncertainty, which poses challenges for risk analysis: Climate change has a potentially non-linear behavior, with complex linkages and the potential for tipping points, as well as a long-term, time-varying nature (Reinders et al., 2023b). While climate scenarios, such as those published by the IPCC or the NGFS, help to account for these characteristics of climate change, challenges remain (IPCC, 2023a; Reinders et al., 2023b).

For these reasons, assessing climate change requires the consideration of the interactions between climate change, macroeconomic variables, environmental policies, and the financial

system. Furthermore, risks arising from climate change require a more extended observation period to reliably assess the risk (Campiglio et al., 2018).
An additional challenge in analyzing climate risk is the incorporation of endogeneity and heterogeneity (Battiston et al., 2021): Individual banks are exposed to unique climate-related financial risks due to the individual regions, markets, and broader macroeconomic conditions in which they operate. This heterogeneity makes it critical for banks and supervisors to select individually appropriate variables or models to assess these risks (Basel Committee on Banking Supervision, 2021a). Another challenge is incorporating the second-round effects of shocks (Farmer et al., 2022).
Further, there is a problem of comparability between stress tests: Although there are several studies and stress tests analyzing the impact of climate risk on financial stability, there are significant differences in methodology and a lack of integration, which complicate comparability (Daumas, 2023).
Also, stress tests rely on assumptions and specific scenarios (Baudino et al., 2018).
Another limitation is the lack of data availability: Stress tests may have limited data granularity and quantity and lack of standardized climate data information, which are often unavailable, inaccessible, or incomplete to researchers (Battiston et al., 2021; Campiglio et al., 2018).

2.3. Research Gaps and Formulation of Research Questions

The literature review emphasizes the importance of stress tests to assess the impact of climate change on financial stability and highlights the limitations of current climate stress testing methodologies.
One approach that overcomes many of those limitations is the market-based climate stress testing methodology introduced by Jung et al. (2023), which estimates the variable CRISK of financial institutions, representing *"the expected capital shortfall [...] under a climate stress scenario"* (Jung et al., 2023, pp. 2–3).
This market-based methodology addresses challenges in previous studies, such as changes in risk perception by estimating risk dynamically and the lack of data availability, by relying only on publicly available market data. It further addresses the issue of heterogeneity raised by the Basel Committee on Banking Supervision (2021a), as the methodology can be applied to individual banks as well as the aggregated banking system. Further, the market-based approach enables the authors to reflect any transition risk drivers in CRISK, as any driver can be reflected in market perceptions.

However, to my knowledge, the approach of Jung et al. (2023) or a similar market-based top-down climate stress test focusing on financial institutions within the Eurozone has not yet been published. Thus, the empirical analysis of this thesis aims to fill this research gap by analyzing the magnitude and distribution of CRISK in the Eurozone, analyzing 237 publicly listed financial institutions over an observation period from 2003 to 2022.
Based on this research gap and the literature review, the following main research question will be tested:

Research Question: *How does climate-related transition risk impact financial institutions and systemic risk within the Eurozone, and what are the dynamic trends and concentration patterns associated with climate-related risks?*

To explore this research question in further detail, the following sub-research questions will be analyzed:

Research Question 1.1: *How does the average Climate Beta of the financial institutions in the data sample develop over the observation period?*
Research Question 1.2: *Do the financial institutions in the data sample exhibit a positive aggregate CRISK and MCRISK, and how does the aggregate CRISK and MCRISK of the financial institutions in the data sample change over the observation period?*
Research Question 1.3: *Are CRISK and MCRISK concentrated in specific companies, industries, or countries within the data sample?*
Research Question 1.4: *How do CRISK and MCRISK of financial institutions in the dataset evolve in times of economic recessions and in response to exogenous shocks such as the onset of financial crises, climate policy shifts, and increased economic losses due to natural disasters?*

3. Methodology

This section presents the data sample of the empirical study and the theoretical approach in detail.

The empirical study in this thesis applies a market-based top-down methodology for climate stress testing introduced by Jung et al. (2023) to 237 listed financial institutions in the Eurozone, analyzing the effect of climate transition risk on publicly listed financial institutions in the Eurozone by estimating the variable *CRISK*, representing "the expected capital shortfall […] under a climate stress scenario" (Jung et al., 2023, pp. 2–3).

CRISK is estimated as follows: First, a *Stranded Asset Portfolio* $CF_{Str,t}$ is constructed as a proxy for transition risk. Based on this proxy, time-varying *Climate Betas* $\beta_{it}^{Climate}$ of the observed financial institutions are estimated through a rolling regression of the company returns on the Stranded Asset Portfolio return $r_{CF_{Str},t}$, representing the sensitivity of company returns to returns of $CF_{Str,t}$. Next, *CRISK*, is estimated, which is a function of each financial institution's market value of equity E_{it}, book value of debt D_{it}, total capital ratio k, Climate Betas $\beta_{it}^{Climate}$, and a climate stress scenario θ.

The analyzed *climate stress scenario* θ is a 50% decline in the return of the Stranded Asset Portfolio over a six-month period. To analyze the systemic risk to the financial sector in the Eurozone, $\Sigma CRISK$, representing the aggregate CRISK of all financial institutions, is calculated. To isolate the impact of climate stress on the expected shortfall, marginal CRISK *MCRISK* is further calculated, representing the difference of CRISK compared to the expected capital shortfall in a non-stressed scenario (Jung et al. 2023).

3.1. Data Sample Construction

To apply the stress test methodology utilized by Jung et al. (2023) to the Eurozone, a sample of all financial institutions with their corporate headquarters in the Eurozone is analyzed. The final data sample of financial institutions encompasses 237 companies and covers a 20-year time horizon, ranging from January 1st 2003, to December 31st 2022.

All financial data for the required variables was retrieved from Datastream and Refinitiv Eikon (Thomson Reuters Refinitiv, 2023). The data analysis was conducted using Stata, Python, and Excel software.

3.1.1. Financial Institutions

This section presents the financial institutions included in the analysis, which consist of all publicly listed companies with corporate headquarters in one of the 20 countries within the

Eurozone (European Union, 2023) and categorized under the GICS industry "*Banks*" or "*Capital Markets*" (MSCI, 2023). The relevant companies were identified using the *Screener* function provided by Refinitiv Eikon, and the mentioned criteria were applied as of July 7th, 2023. The sample of companies includes active and inactive firms to avoid survivorship bias. Applying the criteria mentioned above in the Refinitiv screener resulted in 249 qualifying companies. Subsequently, for these firms, all the variables required for the estimation of CRISK were retrieved from Datastream on a daily basis for the observation period. A description of the retrieved variables is given in Table 1. All data is denominated in Euros.

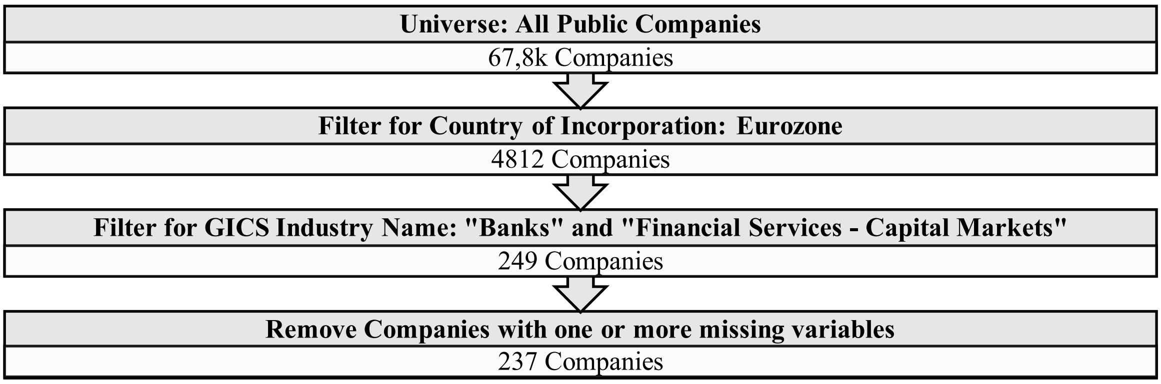
Table 1: *Datastream Variables*

Variable	Symbol	Description
Total Return Index	RI	RI represents a theoretical growth in the value of a share starting from a base date where RI=100. RI assumes that dividends are reinvested to buy additional units of equity. The variable is retrieved in Euros.
Market Capitalization	WC08001	Market capitalization is calculated annually for a company at the fiscal year and date and represents the closing price of the company´s stock on that date, multiplied by the number of common shares outstanding. The variable is retrieved in thousands of Euros.
Total Liabilities	WC03351	Total Liabilities include all long- and short-term obligations that a company must satisfy. The variable is retrieved in thousands of Euros.
Market Value (Capital)	MV	Market Value equals the share price of a company multiplied by the number of ordinary shares issued, representing the market capitalization. The variable is retrieved in millions of Euros.

Source: Thomson Reuters Refinitiv (2023)

Following the data retrieval for the 249 companies, those with missing data for one or more required variables over the entire observed period were excluded, resulting in a remaining dataset of 237 companies. In addition, the dataset was adjusted to include inactive companies until their inactive date. As not all variables were available for all companies on all days, for example because a company did not exist for the entire period or was publicly traded, the panel dataset is imbalanced. The screening methodology is shown schematically in Figure 1.
Further, a list of all analyzed financial institutions is available in the Appendix in Section 8.2.

Figure 1: *Financial Institutions Screening Methodology*



Source: Thomson Reuters Refinitiv (2023)

Table 2 shows an overview of the analyzed GICS industries and subindustries and the distribution of companies over these subindustries by number and market capitalization in the data sample. Further, Section 8.3 in the Appendix shows an overview of the observed countries and the distribution of observed companies by market capitalization.

Table 2: *Observed Companies by GICS Industries and Subindustries*

GICS Industry Banks					
Subindustry	*GICS Subindustry Code*	*# Companies*	*(%)*	*MV*	*(%)*
Diversified Banks	40.101.010	63	*(26,6%)*	538,73	*(86,8%)*
Regional Banks	40.101.015	18	*(7,6%)*	2,87	*(0,5%)*

GICS Industry Financial Services – Capital Markets					
Subindustry	*GICS Subindustry Code*	*# Companies*	*(%)*	*MV*	*(%)*
Asset Management & Custody Banks	40.203.010	122	*(51,5%)*	25,82	*(4,2%)*
Diversified Capital Markets	40.203.030	3	*(1,3%)*	31,91	*(5,1%)*
Financial Exchanges & Data	40.203.040	5	*(2,1%)*	18,09	*(2,9%)*
Investment Banking & Brokerage	40.203.020	26	*(11,0%)*	2,91	*(0,5%)*

MV: *represents the average aggregate MV per subindustry in billion euros.*

Source: Thomson Reuters Refinitiv (2023)

3.1.2. Independent Variables for Climate Beta Estimation

To perform the Climate Beta estimation, a stranded asset stock index and a market stock index are required to construct the Stranded Asset Portfolio $CF_{Str,t}$. Further, the market index is also applied as an independent variable in the subsequent regressions for estimating market betas of the data sample. The selected fossil fuel stock index and market index to construct $CF_{Str,t}$, due to its availability during the entire observation period, are presented in Table 3:

Table 3: *Variables for Stranded Asset Portfolio*

Variable	Index Name	RIC	Abbreviation
Stranded Asset Index	WORLD-DS Oil, Gas, Coal	OILGCWD	$FSL_{\ t}$
Market Index	ISHARES MSCI EUROZONE ETF	U:EZU	MKT_t

Source: Thomson Reuters Refinitiv, 2023

3.2.Theoretical Approach

This section presents the theoretical approach of the market-based top-down climate stress test methodology applied to the presented data sample by first explaining the construction of the Stranded Asset Portfolio $CF_{Str,t}$, followed by the Climate Beta $\beta_{it}^{Climate}$ estimation, and finally, the CRISK estimation, representing the expected capital shortfall of the observed financial institutions.

3.2.1. Stranded Asset Portfolio

To measure the impact of transition risk on financial stability, a Stranded Asset Portfolio $CF_{Str,t}$, is constructed, which represents transition risk, serving as a climate transition risk factor. To model such a climate transition risk factor, Jung et al. (2023) applied the Stranded Asset Index developed by Litterman and WWF (Litterman, 2023), which holds long positions consisting of fossil fuel ETFs[6], representing the Stranded Asset Index $FSL_{\ t}$ and a short position in the SPDR S&P 500 ETF Trust, representing the market index MKT_t.

The *rationale behind the Stranded Asset Portfolio* $CF_{Str,t}$ is that the portfolio's return is a valuable proxy measure to reflect current market expectations on future transition risks. Thus, it is anticipated to have a lower performance than the market in the transition to a low-carbon economy. Consequently, higher transition risk is associated with a decrease of the portfolio return (Jung et al., 2023).

[6] The long position consists of 30% of the Energy Select Sector SPDR ETF and 70% of the VanEck Vectors coal ETF

The return index of the iShares MSCI Eurozone ETF is used as a *proxy for the market index* MKT_t, as the analysis focuses on the Eurozone. The ETF aims to track the performance of the MSCI EMU Index, which includes 228 large and mid-cap companies from industrialized countries in the EMU and represents around 85% of the free float-adjusted market capitalization (MSCI Inc., 2023a).

To construct $CF_{Str,t}$, the RI variable was retrieved from Datastream for $FSL_{\ t}$ and MKT_t for each day of the observation period. The resulting Stranded Asset Portfolio $CF_{Str,t}$ holds a long position in the Stranded Asset Index FSL_t and a short position in the market index MKT_t:

(1) $$CF_{Str,t} = FSL_t - MKT_t$$

Source: Jung et al. (2023)

Next, the daily return $r_{I,t}$ for each presented index *I* is calculated over the observation period of the data sample with the following daily return formula:

(2) $$r_{I,t} = \frac{RI_{I,t} - RI_{I,t-1}}{RI_{I,t-1}}$$

Further, the return of the Stranded Asset Portfolio CF_{Str} in *t* is calculated as follows:

(3) $$r_{CF_{Str},t} = r_{Oil\ Gas\ Coal,t} - r_{MKT,t}$$

3.2.2. Climate Beta Estimation

The next step is to estimate the time-varying Climate Beta $\beta_{it}^{Climate}$ by regressing the stock return $r_{FI_{it}}$ of the 237 observed financial institutions on the previously determined return of the climate risk factor $r_{CF_{Str},t}$, and the market return $r_{MKT,t}$. The regression includes $r_{MKT,t}$ as an independent variable to control for other factors that may affect the companies' stock returns and the Climate Beta (Jung et al., 2023).

The estimated Climate Beta measures the sensitivity of the observed financial institutions to the Stranded Asset Portfolio, and consequently transition risk. Thus, a positive beta implies that if the returns of the Stranded Asset Portfolio fall due to an increase in transition risk, the returns of the companies are also expected to fall, highlighting their exposure to climate risk (Jung et al., 2023).

The reasoning behind this is as follows: When transition risk increases, loans made by financial institutions to firms exposed to transition risk face higher credit risk, as firms may have difficulty repaying the loan. If companies default on their loans, the profit of financial institutions is reduced, and therefore, stock returns are expected to fall (Jung et al., 2023).

To perform the regression, first the variable *RI*, representing the daily stock prices of the 237 companies, is retrieved from Datastream. Next, the daily stock return of all companies in the dataset is calculated as:

$$r_{i,t} = \frac{RI_{i,t} - RI_{i,t-1}}{RI_{i,t-1}} \tag{4}$$

The *resulting panel dataset* consists of the independent variables $r_{MKT,t}$ and $r_{CF_{Str},t}$ and the individual company returns $r_{i,t}$ as the dependent variables.

Fixed Beta Regression

To first obtain a comprehensive understanding of the dataset, a fixed beta regression is conducted for both the aggregate dataset and the individual financial institutions *FI*. The regression model for the overall dataset is:

$$r_{FI_{it}} = \beta^{Mkt} r_{MKT,t} + \beta^{Climate} r_{CF_{Str},t} + \varepsilon_i \tag{5}$$

Source: Jung et al. (2023)

The estimated $\beta^{Climate}$ measures the sensitivity of the stock returns *of all financial institutions* to the Stranded Asset Portfolio returns over the entire observation period.

Next, the regression model for the individual financial institutions *FI* is:

$$r_{FI_{it}} = \beta_i^{Mkt} r_{MKT,t} + \beta_i^{Climate} r_{CF_{Str},t} + \varepsilon_i \tag{6}$$

Source: Jung et al. (2023)

The estimated $\beta_i^{Climate}$ measures the sensitivity of the stock return of *each financial institution* to the Stranded Asset Portfolio over the entire observation period.

Rolling window regression

To account for the time-varying nature of transition risk, a time-varying Climate Beta $\beta_{it}^{Climate}$ is estimated with a rolling regression. Rolling regressions estimate the model coefficients by using a fixed window size for the regression and then sliding that window over time over the data set.

In the subsequent analysis, a *one-year rolling window regression, with a step size of one day*, is applied. The average number of observed trading days per year in the data sample is 260,9, which is why a rolling window size of 261 trading days was used to approximate one year. This window size allows for the study of annual changes, mitigates the effects of short-term fluctuations, and facilitates consistent analysis and comparison across years, making it an effective approach for studying temporal dynamics. Because 261 days are required to estimate the rolling beta window, the Climate Betas are available from January 1st, 2004. This is because the first 261 days of the data sample returns serve as the estimation period, and the observation period begins on January 1st 2003. For companies whose share prices were not available until after January 1st, 2003, the estimation of the rolling beta begins 261 trading days after the share price became available. This ensures that a uniform window size of 261 days is used for beta estimation for all companies in the analysis.

This rolling regression was performed daily for each financial institution from January 1st 2004 to December 31st 2022, applying the following rolling window regression:

$$r_{FI_{it}} = \beta_{it}^{Mkt} r_{MKT,t} + \beta_{it}^{Climate} r_{CF_{Str},t} + \varepsilon_i \quad (7)$$

Source: Jung et al. (2023)

The rolling window regressions were estimated in Stata utilizing the *asreg* package by Shah (2023).

3.2.3. Stress Scenarios

A critical aspect of stress testing is the definition of a stress scenario. For a suitable stress test, the shock scenarios should be *"severe, but still plausible"* (Reinders et al., 2023, p.15). The stress scenario θ analyzed is a *50% decline in the Stranded Asset Portfolio return* $r_{CF_{Str},t}$ *over a six-month period*, which represents the 0,03% percentile of the return distribution of $r_{CF_{Str},t}$ within the observation period, following the approach of (Jung et al., 2023):

$$r_{CF_{Str},t,t+6\ months} \leq -50\% \quad (8)$$

Source: Jung et al. (2023)

Additionally, a *sensitivity analysis* for other stress level scenarios, ranging from a 25% to a 90% decline in returns, is performed in Section 4.5.1.

3.2.4. CRISK and MCRISK Estimation

Next, *CRISK* for each financial institution and subsequently, the aggregated CRISK for the financial sector is calculated with the methodology introduced by Jung et al. (2023). *CRISK* represents the expected capital shortfall of financial institutions in the defined stress scenarios and is a function of the market value of equity E_{it}, the book value of debt D_{it} and the Climate

Beta $\beta_{it}^{Climate}$ of a financial institution, as well as the prudential reserve ratio k and a predefined stress scenario θ.

While a positive capital shortfall represents an undercapitalization of the financial institution, a negative shortfall implies a capital surplus (Jung et al., 2023).

Undercapitalization of financial institutions can lead to systemic risk and trigger potential spillover effects of systemic risk to the real economy through the following transmission channel: If a bank is undercapitalized, it may go bankrupt in a stress scenario. If there is an aggregate capital shortfall in the financial system, competitors may be unable to acquire bankrupt financial institutions. This can affect the ability of financial systems to provide credit to the real economy (Brownlees & Engle, 2017).

Variables for calculating CRISK

This analysis assumes a capital ratio of $k = 8\%$ for the estimation of CRISK and in the Eurozone, as the total capital ratio in the Eurozone, regulated in Article 92 of the *EU Capital Requirements Regulation* (CRR), requires financial institutions to fulfill a minimum total capital ratio of 8% (European Parliament and European Council, 2013).

Further, the previously estimated Climate Beta $\beta_{it}^{Climate}$ and the defined stress scenario θ are utilized to calculate CRISK.

The Datastream variable *Market Value (MV)* is utilized to estimate the current market value of equity E_{it} for each financial institution and date. Further, the variable *Total Liabilities* is applied to estimate the book value of debt D_{it} for each financial institution and date (Thomson Reuters Refinitiv, 2023). Total Liabilities are chosen over total debt since a substantial portion of a financial institution's debt comprises its deposits, which are presented separately on the balance sheet. By using total liabilities, a more accurate representation of the actual debt level of each firm is achieved.

Non-stressed CRISK

First, the *non-stressed CRISK*, which represents the expected capital shortfall of a financial institution i in time t, assuming that the climate stress level θ is equal to zero, is calculated by subtracting the market value equity E_{it} of the financial institution from the required capital reserve $k(D_{it} + E_{it})$.

(9) $$CRISK_{it}^{non-stressed} = k(D_{it} + E_{it}) - E_{it} = kD_{it} - (1 - k)E_{it}$$

Source: Jung et al. (2023)

Stressed CRISK

The stressed CRISK, which is the expected capital shortfall per financial institution *conditional on the defined stress scenario*, represented by the decrease of the Stranded Asset Portfolio $CF_{Str,t}$ by 50% over six months, is defined as:

$$(10) \qquad CRISK_{it} = e_t\{CS_{i,t+h} | r_{CF_{Str},t,t+6\,months} \leq -50\%\}$$

Source: Jung et al. (2023)

Next, the long-run marginal expected shortfall $LRMES_{it}$ is defined as the expected arithmetic equity loss of each financial institution under the stress test scenario over six months:

$$(11) \qquad LRMES_{it} = -e_t\{r_{i,t,t+6\,months} | r_{CF_{Str},t,t+6\,months} \leq -50\%\}$$

Source: Jung et al. (2023)

Further, following the methodology of Jung et al. (2023), it is assumed that the liabilities of financial institutions remain constant during the stress scenario. Thus, the stressed CRISK, assuming a climate stress level of $\theta = 50\%$ and a prudential capital ratio of $k = 8\%$, is estimated as:

$$(12) \qquad \begin{aligned} CRISK_{it} &= kD_{it} - (1-k)(1 - LRMES_{it})E_{it} \\ &= kD_{it} - (1-k)E_{it}e^{\beta_{it}^{Climate} \times \log(1-\theta)} \end{aligned}$$

Source: Jung et al. (2023)

Marginal CRISK

The difference between the stressed and non-stressed CRISK is represented by the marginal CRISK $MCRISK_{it}$, which isolates the effect of climate stress on the expected capital shortfall and is calculated as:

$$(13) \qquad MCRISK_{it} = CRISK_{it} - CRISK_{it}^{non-stressed}$$

Source: Jung et al. (2023)

Aggregate CRISK and MCRISK

To calculate the effect of climate change on systemic risk, the aggregated CRISK and MCRISK for all *n=237* observed financial institutions *i* in *t* are calculated as:

$$(14) \qquad \Sigma CRISK_t = \sum_{i=1}^{n} CRISK_{it} \qquad (15) \qquad \Sigma MCRISK_t = \sum_{i=1}^{n} MCRISK_{it}$$

Source: Jung et al. (2023)

$\Sigma CRISK$ represents the capital injection the financial system would require in times of the climate stress scenario. $\Sigma MCRISK$ isolates the amount of capital injection that is caused by the climate stress scenario itself (Jung et al., 2023).

4. Results

This section discusses the results of the analysis applying the presented methodology.
First, the summary statistics of the independent and dependent variables are presented, followed by the results of the regressions to estimate the Climate Beta. Next, the estimated CRISKs are evaluated, focusing on a time series as well as a cross-sectional analysis of the individual and aggregate CRISK and MCRISK. Finally, two extensions of the analysis are presented, one focusing on an event study analyzing the impact of transition risk events on $CF_{Str,t}$ returns and one focusing on the impact of natural disasters on MCRISK.

4.1. Summary Statistics

4.1.1. Summary Statistics of Independent Variables

This section presents the summary statistics of the independent variables in the dataset, $r_{MKT,t}$ and $r_{CF_{Str,t}}$, over the observation period from January 1st 2003, to December 31st, 2022. Further, it presents how the cumulative return of the Stranded Asset Portfolio $CF_{Str,t}$, the Market Portfolio MKT_t, and the Stranded Asset Index FSL_t develops.

Summary Statistics

Table 4 provides summary statistics of daily returns for the explanatory variables $r_{MKT,t}$ and $r_{CF_{Str,t}}$ during the observation period. Both variables consist of 5218 observations each, representing an average of 260,9 trading days per year.
The *mean daily return* for MKT_t is 0,0322%, a significantly higher value than$CF_{Str,t}$'s mean daily return of 0,0048%. One possible explanation for this discrepancy is the composition of $CF_{Str,t}$, which includes the Stranded Asset Index and a short position in tMKT_t, as presented in Section 3.2.1.
Additionally, the *standard deviation* of $r_{CF_{Str,t}}$ is lower than that of $r_{MKT,t}$, indicating that CF_t's daily returns exhibit less variability around the mean.

Both $r_{MKT,t}$ and $r_{CF_{Str,t}}$ exhibit *negative skewness*, which suggests that their distributions have a tail on the left side, implying that there are more frequent occurrences of small positive returns and less frequent but larger negative returns.

Additionally, both $r_{MKT,t}$ and $r_{CF_{Str,t}}$ display a *positive excess kurtosis* and follow a *leptokurtic distribution*. A leptokurtic distribution is characterized by large tails and a narrow center, indicating a higher likelihood of more significant outliers than a normal distribution.

Table 4: *MKT_t and $CF_{Str,t}$ Summary Statistics for Daily Return*

	Market Portfolio MKT_t	**Stranded Asset Portfolio $CF_{Str,t}$**
Mean	0,000322	0,000048
Median	0,000649	0,000025
Standard Deviation	0,014762	0,011549
Sample Variance	0,000218	0,000133
Excess Kurtosis	9,919873	4,839823
Skewness	-0,153282	-0,112364
Range	0,268178	0,160484
Minimum	-0,125129	-0,089547
Maximum	0,143049	0,070937
Count	5218	5218

Source: Own calculation

Distribution of returns

To test the distribution of daily returns for both MKT_t and $CF_{Str,t}$ for normality, a *skewness and kurtosis test for normality* is carried out, utilizing the method introduced by D'Agostino et al. (1990). The results in Table 18 in Section 8.4.1 in the Appendix show that the p-values obtained for both variables indicate a difference in skewness and kurtosis compared to that of a normal distribution, significant at the 1% significance level. Therefore, it can be concluded that the daily returns of MKT_t and $CF_{Str,t}$ do not conform to a normal distribution.

Figure 2 shows the histogram distributions of daily returns of MKT_t, while Figure 3 shows the respective distribution for $CF_{Str,t}$.

Figure 2: *Histogram of MKT Return*

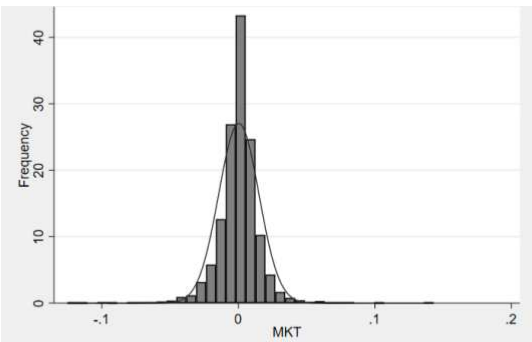
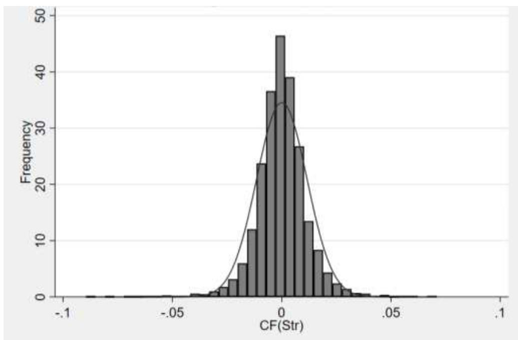


Figure 3: *Histogram of CF(Str) Return*



Source: Own illustration

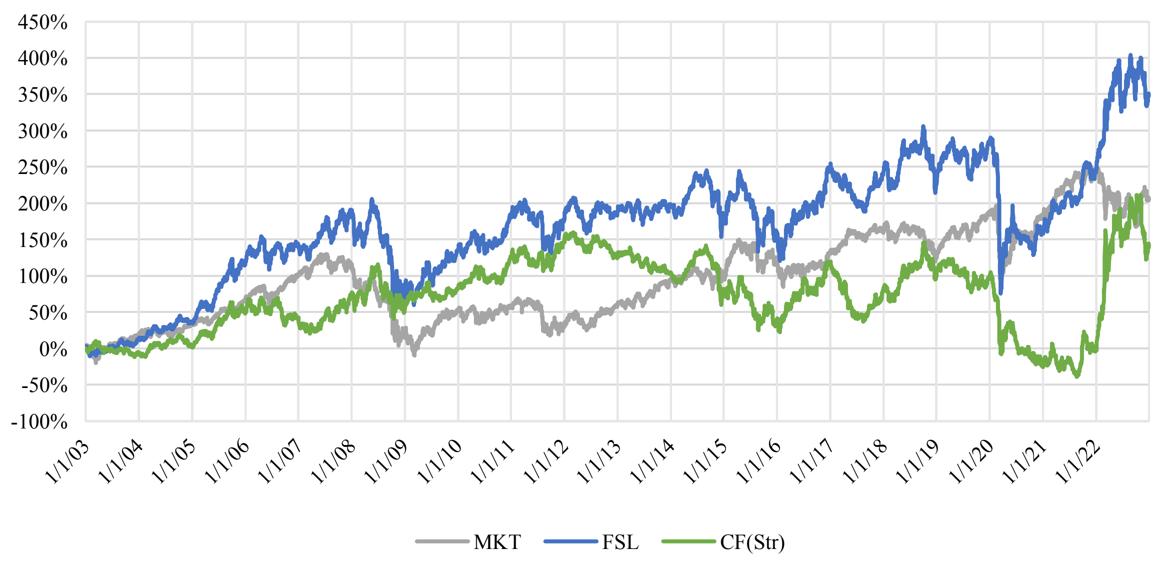
Correlation of $r_{MKT,t}$ and $r_{CF_{Str,t}}$

A correlation analysis in in Section 8.4.1 in the Appendix reveals a *statistically significant moderate negative correlation* of -0.547 between the daily returns of the independent variables $r_{MKT,t}$ and $r_{CF_{Str,t}}$, significant at the 10% level. One plausible explanation for this negative correlation is again related to the composition of the Stranded Asset Portfolio, which includes a short position in the Market Portfolio, and may contribute to the observed negative relationship between $r_{MKT,t}$ and $r_{CF_{Str,t}}$.

Cumulative returns

Figure 4 displays the cumulative return of the Stranded Asset Portfolio $CF_{Str,t}$ the Market Portfolio MKT_t, and the Stranded Asset Index $FSL_{\ t}$. The graph highlights that $FSL_{\ t}$ itself exhibits a strong outperformance compared to MKT_t throughout the observed period, with a cumulative return of 347,45%. However, since $CF_{Str,t}$ not only consists of $FSL_{\ t}$, but also of a short position in MKT_t, the overall cumulative return of $CF_{Str,t}$ is lower with a cumulative return of 143,45%, which is in line with the mean returns presented before in Table 4. The cumulative return of MKT_t is 204,00%.

Figure 4: *Cumulative Return of Stranded Asset Portfolio and Market Portfolio*



MKT: *Cumulative return of market portfolio*
FSL: *Cumulative return of stranded asset index*
CF(Str): *Cumulative return of stranded asset portfolio*
Source: Own illustration

4.1.2. Summary Statistics of Dependent Variables

This section presents the summary statistics, distribution and cumulative return of the stock returns of the analyzed financial institutions.

Summary statistics

Table 5 provides summary statistics of the daily stock returns of the 237 publicly listed financial institutions *FI* over the observation period from January 1st 2003, until December 31st 2022. Certain financial institutions were not publicly listed for the entire observation period. As a result, their daily returns were only available from the IPO date onwards. In addition, some companies ceased to exist or went private during the observation period, which limited the observation of daily returns to the period when they remained listed. As a result of these factors, the dataset comprises a total of 949.222 daily return observations, averaging approximately 4.005,16 observations per company, which is lower than the 5218 daily return observations available for each of the independent variables, making the panel dataset unbalanced.

The summary statistics reveal an overall mean of all daily returns of the observed financial institutions of 0,389%, which is significantly higher than the mean return of MKT_t (0,032%) and $CF_{Str,t}$ (0,005%). However, this higher mean comes with a significantly higher overall standard deviation of 2,090 compared to MKT_t (0,015) and $CF_{Str,t}$ (0,012).

Moving on to the between-group summary statistics, the standard deviation of the mean (between) is 0,038. This metric measures how much individual financial institutions' average daily return varies around the entire dataset's overall mean return.

Moreover, the range of the average daily return value among all company returns is narrower than the range of the individual returns. One reason for this reduced range is that the standard deviation is based on the average daily return of all financial institutions compared to the overall mean.

Table 5: *Summary Statistics for Daily Return of Financial Companies*

Variable		Obs	Mean	Std. Dev.	Min.	Max.
$r_{FI_{it}}$	Overall	N = 949222	0,00389	2,090	-1,000	1824,111
	Between	n = 237		0,038	-0,003	0,590
	Within	$\bar{T}$ = 4005,16				

Source: Own calculation

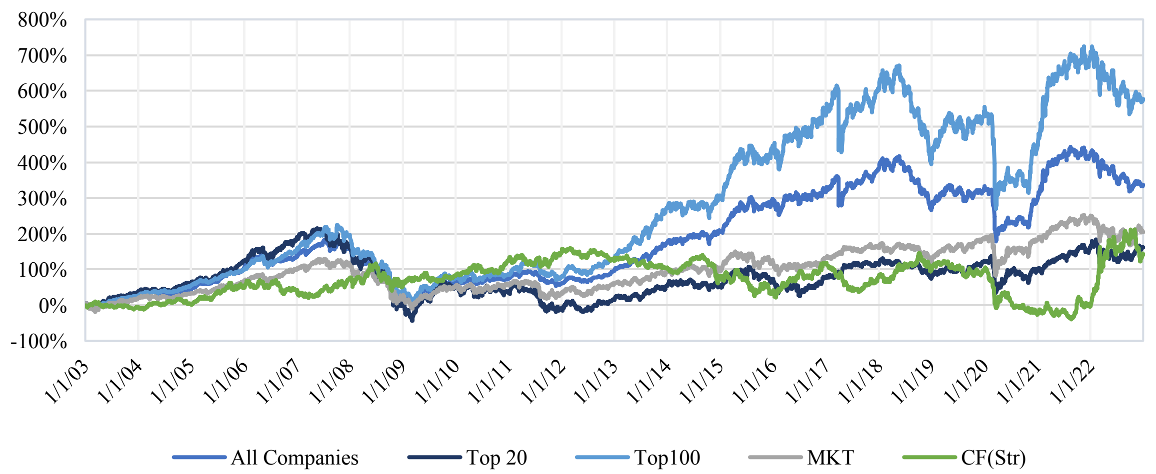
Return Distribution

The histogram in Section 8.4 in the Appendix shows the daily return distribution of all financial companies and reveals the presence of several extreme outliers in the distribution. To address the potential bias stemming from these extreme values in the subsequent analysis, a *winsorization procedure* was implemented on the dependent variable at the 5th percentile. This approach involves replacing values beyond the 5th and 95th percentiles with their respective percentile values, effectively eliminating the undue influence of outliers. Figure 20 in Section 8.4.2 in the Appendix illustrates the distribution of the dependent variable's returns after the winsorization process.

Cumulative returns

Figure 5 displays the cumulative equal-weighted return of all observed financial institutions along with the top 100 and top 20 companies ranked by market capitalization as of December 31st 2022 for the observed period from January 1st 2003 to December 31st 2022.
The cumulative equal-weighted return of all observed financial institutions by the end of the observation period amounts to 336,09%. In comparison, it reaches 577,46% for the top 100 firms and 160,79% for the top 20 firms. Notably, the average cumulative return of all companies and the top 100 companies outperforms both MKT_t (204,00%) and $CF_{Str,t}$ (143,45%).

Figure 5: *Cumulative Equal-Weighted Return of Observed Companies*



MKT: *Cumulative return of market portfolio*
CF(Str): *Cumulative return of stranded asset portfolio*
Top20 / Top 100: *Cumulative return of top financial institutions by market capitalization as of 31/12/2022*
Source: Own illustration

Distribution of Financial Institutions by Country and Subindustry

Figure 6 provides an overview of the percentage distribution of the financial industries in the individual countries, measured by their share of total market capitalization as of December 31st 2022.

The chart shows that from the analyzed companies, the financial institutions listed in France have the highest aggregate market capitalization, followed by Spain, Italy, Germany, and the Netherlands. It is important to note that the market value of equity is a crucial variable in the calculation of CRISK. Consequently, countries with a higher aggregate market capitalization, such as those mentioned above, can be expected to have a higher overall CRISK due to the magnitude of their financial sector.

In addition, Figure 7 provides a visual representation of the distribution of market capitalization across the examined sub-industries. The data presented in the figure illustrate that the diversified banks subindustry accounts for a significant portion, 79,9%, of total market capitalization. This result strongly suggests that the diversified banks subindustry will likely have the most considerable influence on CRISK.

Figure 6: *Distribution of Market Capitalization by Country*

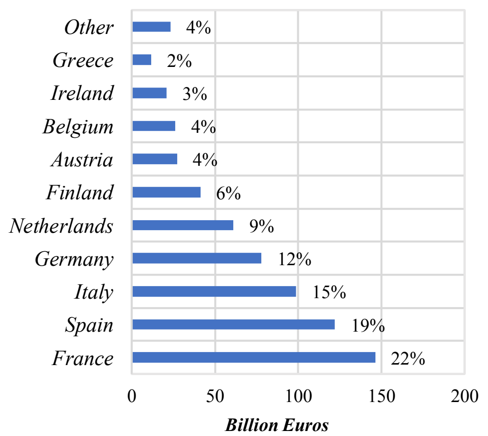
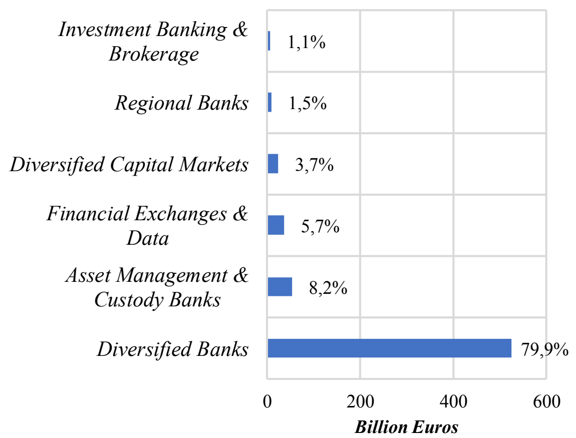


Figure 7: *Distribution of Market Capitalization by Subindustry*



The depicted graphs show the ascending distribution of aggregate market capitalization as of December 31st 2022 of the observed companies by country in Figure 6 and by subindustry in Figure 7 in billion euros.

Source: Own illustration

4.2.Regressions

This section presents the results of the fixed beta and rolling window regressions that are performed to estimate the Climate Beta $\beta_{it}^{Climate}$.

4.2.1. Fixed Beta Regression

Statistical Tests

First, a fixed effects as well as a random effects regression for the entire sample with the returns $r_{FI_{it}}$ a dependent variable, and $r_{MKT,t}$ and $r_{CF_{Str,t}}$ as independent variables is performed.
Table 23 in Section 8.6 in the Appendix includes the fixed effects regression results for all 237 analyzed companies, while Table 24 depicts the random effects regression results.
To test whether fixed effects regression or random effect regressions are more suitable for the data sample, a *Hausman test* (Hausman, 1978) is performed. The results presented in Table 20 in Section 8.5 in the Appendix show that the p-value of the Hausman test is greater than 0,05. Thus, the null hypothesis cannot be rejected, and consequently, a random effects regression is more appropriate.
Additionally, the significance of random effects is examined utilizing the *Breusch-Pagan Lagrange Multiplier test* (Breusch & Pagan, 1980). The test results in Table 21 in Section 8.5 in the Appendix reveal a p-value below 0,05, allowing the rejection of the null hypothesis and confirming the significance of random effects. Thus, the appropriateness of the random effects model is established.
Subsequently, autocorrelation in the data sample is tested with the *Woolridge test* (Woolridge, 2010). The results in Table 22 in Section 8.5 in the Appendix show that the null hypothesis of no serial correlation is strongly rejected. As a solution, the random effects regression is executed again, incorporating *Eicker-Huber-White Robust Standard Errors*, which also control for heteroskedasticity in the dataset.

Fixed Beta Regression

The results of the modified random effects regression with robust standard errors are displayed in Table 6, ensuring the robustness of the analysis and providing reliable estimates of the regression parameters. The coefficients of both independent variables obtained from this regression on the full data sample are statistically significant at the 1% significance level. The fixed Climate Beta $\beta^{Climate}$ represents the coefficient of $r_{CF_{Str,t}}$ and has a value of 0,103 during the observation period.

The Climate Beta quantifies the sensitivity of the financial institutions' stock returns to the Stranded Asset Portfolio returns. This means, a 1% change of the Stranded Asset Portfolio is associated with a 0,103% change in the financial institutions returns for the whole data sample. The coefficient of $r_{MKT,t}$ is also statically significant at a significance level of 1%, with a coefficient of 0,217.

Table 6: *Random Effects Regression Results, Robust Standard Errors*

Variable	Coefficient	Std. Err.	t-value	p-value	[95% Confidence Interval]		Sig.
$r_{MKT,t}$	0,217	0,016	13,91	0,000	0,186	0,247	***
$r_{CF_{Str,t}}$	0,103	0,006	17,66	0,000	0,091	0,114	***
Constant	0,000	0,000	-0,28	0,779	0,000	0,000	

Mean dependent variable	0,000	Std. Dev. dependent variable	0,016
		Number of observations	949222
		Number of groups	237
R-squared	Within = 0,0288	Observations per group	Min= 111
	Between = 0,0019		Avg= 4005,2
	Overall = 0,0288		Max= 5218
Wald Chi-square	312,74	Prob > chi2	0,00

*Significance levels: *** p<0.01, ** p<0.05, * p<0.1*

Source: Own calculation

Individual Beta Regression

Subsequently, the estimation of fixed betas $\beta_i^{Climate}$ is conducted individually for all financial institutions under analysis, employing random effects and robust standard errors. The regression results for the top 20 financial companies in the Eurozone, ranked by market capitalization as of December 31st 2022, are presented in Table 7. As indicated in Table 7, the average $\beta_i^{Climate}$ of these top 20 companies is 0,207, which is significantly higher than the Climate Beta of the entire data sample, which is 0,103, indicating greater sensitivity to transition risk.

Table 7: *Individual Fixed Beta Regression of Top 20 Companies*

Company Name	Ticker	β^{Mkt}	$\beta^{Climate}$	R^2	Rank
BNP Paribas SA	BNPP.PA	0,727	0,210	0,301	1
Banco Santander SA	SAN.MC	0,743	0,247	0,317	2
ING Groep NV	INGA.AS	0,776	0,266	0,303	3
Intesa Sanpaolo SpA	ISP.MI	0,681	0,123	0,270	4
Nordea Bank Abp	NDAFI.HE	0,643	0,293	0,263	5
Banco Bilbao Vizcaya Argentaria SA	BBVA.MC	0,716	0,228	0,303	6
Credit Agricole SA	CAGR.PA	0,718	0,250	0,265	7
Deutsche Boerse AG	DB1Gn.DE	0,477	0,201	0,154	8
Caixabank SA	CABK.MC	0,596	0,228	0,207	9
UniCredit SpA	CRDI.MI	0,695	0,167	0,233	10
Kbc Groep NV	KBC.BR	0,662	0,253	0,217	11
Deutsche Bank AG	DBKGn.DE	0,757	0,276	0,277	12
Societe Generale SA	SOGN.PA	0,753	0,222	0,277	13
Erste Group Bank AG	ERST.VI	0,623	0,240	0,187	14
ABN Amro Bank NV	ABNd.AS	0,675	0,207	0,238	15
Commerzbank AG	CBKG.DE	0,723	0,249	0,215	16
Amundi SA	AMUN.PA	0,607	0,036	0,247	17
Aib Group PLC	AIBG.I	0,436	0,221	0,061	18
Bank of Ireland Group PLC	BIRG.I	0,551	0,246	0,108	19
Banca Fineco SpA	FBK.MI	0,581	0,009	0,193	20
Average	**-**	***0,657***	***0,207***	***0,232***	**-**

Rank: *Represents rank by Market Capitalization as of December 31st 2022*

Source: Own calculation

4.2.2. Rolling Window Regression

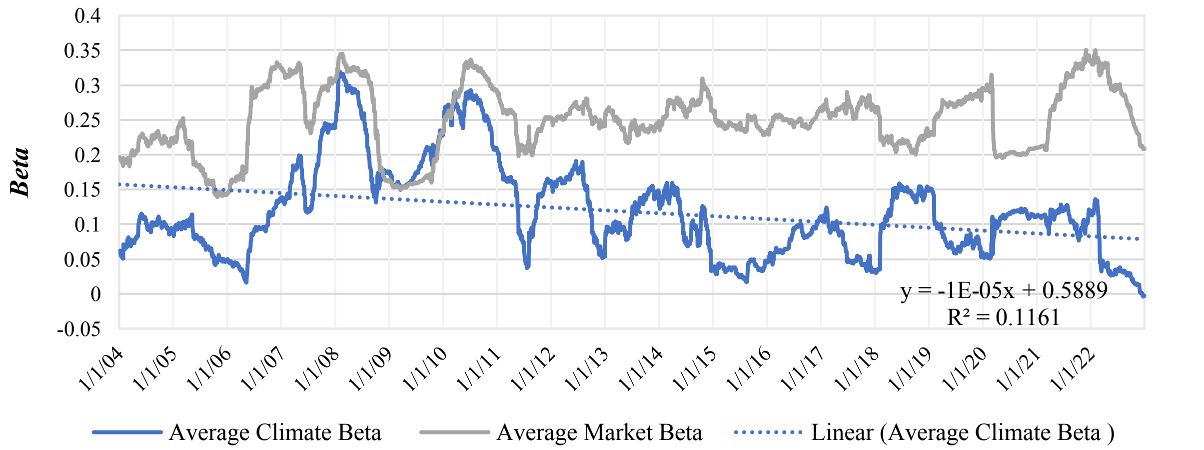
To estimate the time-varying Climate Betas $\beta_{it}^{Climate}$ for the CRISK estimation, a rolling window regression with random effects and Newey-West robust standard errors is performed, with a rolling window size of 261 days and a step size of one day. Figure 8 shows the average rolling Climate Beta $\beta_{it}^{Climate}$ and Market Beta β_{it}^{Mkt} for all analyzed financial institutions over the analyzed period from January 1st 2004 to December 31st 2022.

The average rolling Climate Beta $\beta_{it}^{Climate}$ exhibits a mean of 0,1179 with a standard deviation of 0,0009, suggesting a positive moderate overall sensitivity. Additionally, Figure 8 illustrates that the average rolling Climate Beta remains positive throughout the entire period until December 2022. The pattern depicted in Figure 8 indicates occasional sudden spikes in Climate Beta values, which may be attributed to external shocks affecting the financial institutions.

Across the observation period, the average $\beta_{it}^{Climate}$ in the Eurozone spans from -0,0038 to 0,3191. These significant variations observed in $\beta_{it}^{Climate}$ over time reaffirm the importance of employing a dynamic estimation approach, as previously noted by Jung et al. (2023). However, contrary to expectations, the average $\beta_{it}^{Climate}$ exhibits a downward trend, as indicated by the trend line calculated with a linear OLS regression.

The full summary statistics and a correlation analysis for the rolling Climate Beta and the rolling Market Beta are available in the Appendix in Section 8.7 and the individual rolling betas of the top 20 companies by market capitalization are shown in the Appendix in Section 8.8.

Figure 8: *Average Rolling Betas*



Source: Own illustration

4.3.CRISK and MCRISK Evaluation

This section presents and analyzes the estimated aggregate CRISK and MCRISK values for the entire observation period, calculated based on the formula previously presented in the methodology section, incorporating a capital ratio of $k = 8\%$ and a climate stress level of $\theta = 50\%$. Further, the following sections examine the time-series and cross-sectional trends in both CRISK and MCRISK.

Aggregate CRISK

Table 8 provides an overview of the summary statistics for $\Sigma CRISK$ of all observed financial institutions over the entire observation period. The results show that $\Sigma CRISK$ remained positive throughout the observation period, with an average value of EUR 594,39 billion.

Table 8: *Summary Statistics Aggregate CRISK (Billion Euros)*

CRISK	Mean	Median	Std. Dev.	Min.	Max.	%MV
Top 20	562,39	603,66	202,91	135,32	901,29	123,28%
Top 100	601,81	646,39	235,38	97,96	992,05	112,10%
All	**594,39**	**640,46**	**239,68**	**78,65**	**990,88**	**107,77%**

%MV: *represents the average share of aggregate CRISK relative to aggregate MV.*
Source: Own calculation

Aggregate Marginal CRISK

In addition, Table 10 presents the summary statistics of $\Sigma MCRISK$ of all observed financial institutions over the entire observation period. The results show a positive mean $\Sigma MCRISK$, suggesting that climate stress increases the overall expected capital shortfall for the observed financial institutions over the observation period. Furthermore, $\Sigma CRISK$ is statistically significantly different from zero at a significance level of 1%.[7]

Table 9: *Summary Statistics Aggregate MCRISK (Billion Euros)*

MCRISK	Mean	Median	Std. Dev.	Min.	Max.	%MV
Top 20	34,85	26,10	24,69	-7,73	108,43	7,96%
Top 100	39,49	29,68	27,96	-8,25	126,03	6,66%
All	**40,42**	**30,42**	**28,48**	**-8,35**	**129,18**	**6,62%**

%MV: *represents the average share of aggregate MCRISK relative to aggregate MV.*
Source: Own calculation

4.3.1. Time-series analysis of CRISK

This section presents the temporal development of $\Sigma CRISK$ and $\Sigma MCRISK$ over the analyzed period. Further, it analyzes changes in the variables in times of recession and after financial crisis shocks.

Aggregate CRISK

Figure 9 illustrates the aggregate stressed and non-stressed $\Sigma CRISK$ for all observed companies. The graph reveals that the stressed $\Sigma CRISK$ exceeds the non-stressed $\Sigma CRISK$ throughout most of the observed period, indicating a higher risk exposure under climate stress scenarios. The stressed $\Sigma CRISK$ exhibits considerable fluctuations, as is also shown by the standard deviation of EUR 239,68 billion over the observation period. The maximum $\Sigma CRISK$ during the observation period is measured on 21st April 2020, with an aggregate $\Sigma CRISK$ of EUR 990,88 billion. $\Sigma CRISK$ further shows an overall upward trend, as indicated by the trend line calculated with a linear OLS regression with a slope of 0,074.
The latest measured $\Sigma CRISK$ as of December 31st, 2022, is EUR 811,12 billion, indicating a 36,46% increase compared to the average $\Sigma CRISK$ observed throughout the observation period.

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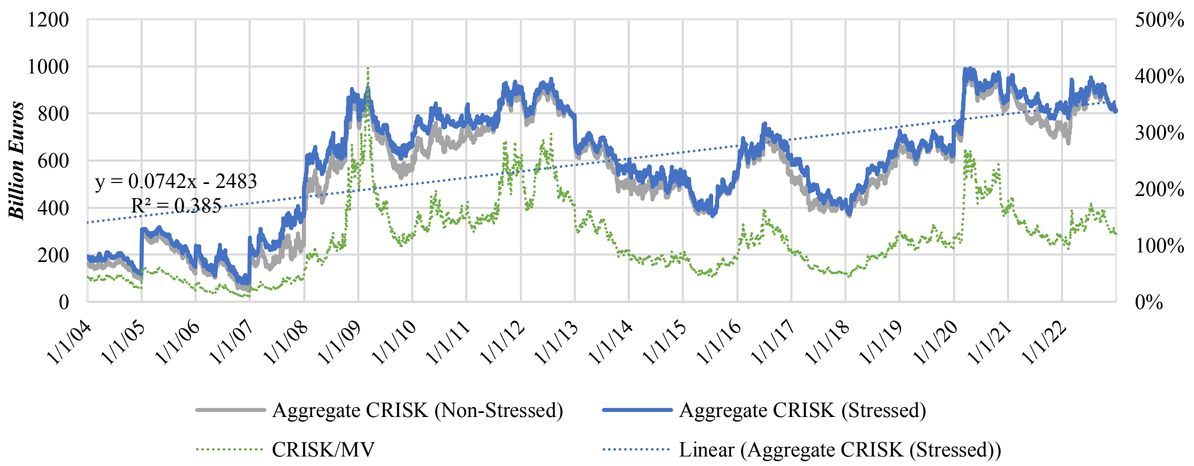
[7] A t-test is employed to evaluate the statistical difference between the aggregate marginal CRISK during the observation period and zero, where the null hypothesis is that aggregate MCRISK equals zero. The result of the t-test yields a p-value of 0,00, indicating that aggregate MCRISK is statistically significantly different from zero at a significance level of 1%.

The occurrence of spikes in $\Sigma CRISK$ could be partially attributed to external shocks affecting financial institutions. However, it is crucial to acknowledge that significant fluctuations that occur at the beginning of each year may also be because the variable D_{it} is commonly only available annually, whereas CRISK is estimated daily. Consequently, when D_{it} changes at the beginning of a new year, it may have a noticeable impact on CRISK values. Furthermore, the graph illustrates the progression of $\Sigma CRISK$ in relation to the aggregate market capitalization, accounting for fluctuations throughout the observation period and indicating a minor positive trend over this period, as calculated using a linear OLS regression.

***Figure 9**: Aggregate CRISK Stressed and Non-Stressed*



This graph shows $\Sigma CRISK$ in bn euros on the left y-axis and the share of $\Sigma CRISK$ to ΣMV on the right y-axis.
Source: Own illustration

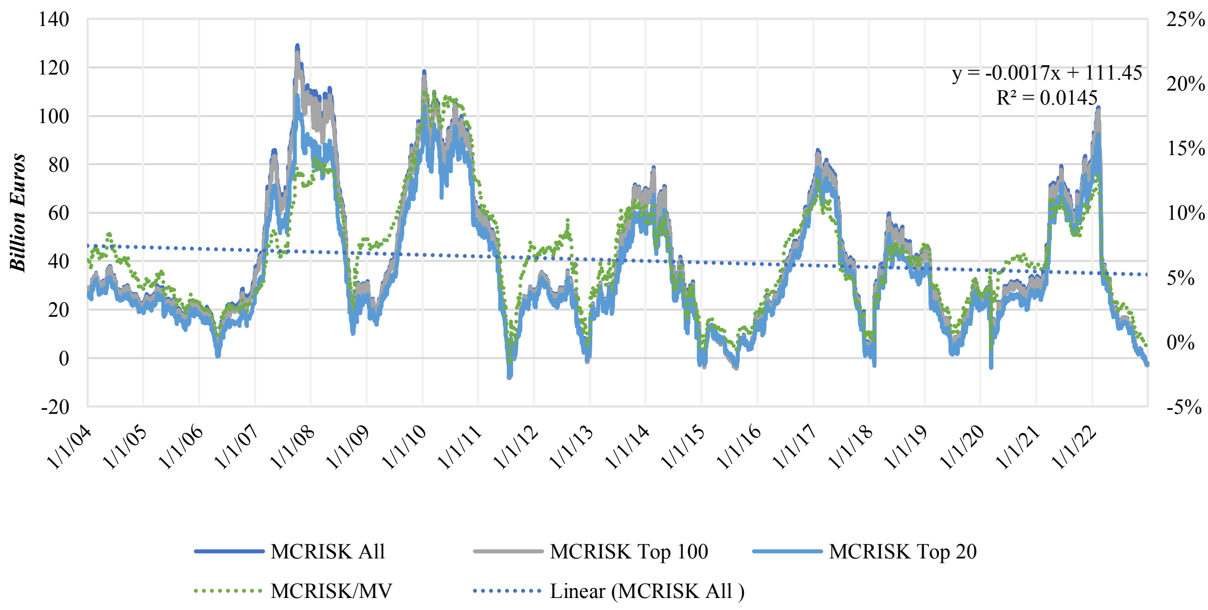
Aggregate Marginal CRISK

Figure 10 illustrates the trend in $\Sigma MCRISK$ during the observation period. It is positive for 98,06% of the observed period, indicating a notable rise in risk on average under the climate stress scenario. Additionally, the figure reveals that most of the $\Sigma MCRISK$ pertains to the top 20 companies by market capitalization as of December 31st 2022. This pattern will be further explored in the cross-sectional analysis in Section 4.3.2.

The pattern of $\Sigma MCRISK$ shown in Figure 10 suggests the presence of occasional sharp spikes that could be due to external shocks affecting financial institutions. The maximum $\Sigma MCRISK$ during the observation period is EUR 129,18 billion, measured on October 5th 2007.

The $\Sigma MCRISK$ shows a slight negative trend with a slope of -0,0017 as computed through OLS Regression. Furthermore, the graph illustrates the development of $\Sigma MCRISK$ in relation to the aggregate MV, to control for fluctuations in MV over the period and also shows a slight negative trend, calculated with a linear OLS regression.

Figure 10: *Aggregate Marginal CRISK*



This graph illustrates Σ*MCRISK in billion euros on the left y-axis and the share of* Σ*MCRISK to* ΣMV *on the right y-axis.*

Source: Own illustration

Development of ΣCRISK and ΣMCRISK during Periods of Recession

This section focuses on the pattern of $\Sigma CRISK$ and $\Sigma MCRISK$ in recession periods in the Eurozone. The identification of recession periods in the Eurozone is based on the definition provided by Eurostat and published in the Business Cycle Clock (Eurostat, 2023). Within the observation period, the Business Cycle Clock identifies three different recession periods:

1. *Period 1:* June 2008 - June 2009
2. *Period 2:* August 2011 - February 2013
3. *Period 3:* April 2020 - July 2020

Section 8.9.1 in the Appendix compares the average $\Sigma CRISK$ in times of recession to non-recession periods, revealing that the $\Sigma CRISK$ increases by 24,01% on average during times of recession, to an average $\Sigma CRISK$ of EUR 710,69 billion, compared to EUR 573,11 billion in times of no recession.[8] One possible explanation for this trend is the undercapitalization of banks in times of crisis, which makes them more vulnerable to market and climate risks.

[8] Figure 22 in Section 8.9.1 in the Appendix further shows the development of CRISK visually, with recession periods highlighted in gray.

A correlation analysis reveals a statistically significant positive relationship between periods of recession and $\Sigma CRISK$, with a correlation coefficient of 0,2098.[9] This finding strongly suggests that $\Sigma CRISK$ significantly increases during periods of recession within the observed timeframe. However, it is important to note that there are other instances where $\Sigma CRISK$ shows significant increases that are not directly related to the presence of a recession, such as in 2016.

To separate the impact of climate risk from market risk, the development of $\Sigma MCRISK$ during times of recession is analyzed, which increases by 25,34% to an average $\Sigma MCRISK$ of EUR 48,72 billion during recession periods, compared to EUR 28,72 billion during periods of no recession. In addition, $\Sigma MCRISK$ shows a statistically significant, albeit weak, positive correlation with a correlation coefficient of 0,1262 regarding the presence of a recession in the Eurozone.[10] $\Sigma MCRISK$ increased significantly during the first recession triggered by the global financial crisis. However, the impact on $\Sigma MCRISK$ appears to be less pronounced during other recessions.

The increase of $\Sigma MCRISK$ during times of recession suggests that, in addition to the market stress in times of crisis, financial institutions are also more exposed to climate risks.

Development of $\Sigma CRISK$ and $\Sigma MCRISK$ during Periods of Financial Crises

The following analysis examines the pattern of $\Sigma CRISK$ and $\Sigma MCRISK$ in different financial crisis shocks compared to pre-crisis levels. Pre-crisis levels are defined as the average $\Sigma CRISK$ and $\Sigma MCRISK$ in the month before each crisis. $\Sigma CRISK$ and $\Sigma MCRISK$ during pre-crisis levels are compared to the averages in the first shock period, defined as the first three months after the onset of the crisis, and to the entire crisis period.

The beginnings of the crisis periods are defined based on the initial shock that leads to the outbreak of various financial crises until the first signs of easing. The selected analyzed crises include the global financial crisis (07/2007-09/2009), the sovereign debt crisis (10/2009-08/2012) and the COVID-19 pandemic (02/2020-12/2022), with the time periods following the respective definitions of Van Riet (2010), Alessi et al. (2019) and Hobelsberger et al. (2023). Figure 11 and Figure 12 show the visual representations of $\Sigma CRISK$ and $\Sigma MCRISK$, respectively, with the crisis periods highlighted.

[9] The correlation analysis CRISK is available in Section 8.9 in the Appendix.

[10] The correlation analysis of $\Sigma MCRISK$ is available in Section 8.9 in the Appendix. Figure 23 in the Appendix further shows the development of $\Sigma MCRISK$ visually, with recession periods highlighted in gray.

***Figure 11**: $\Sigma CRISK$ in Financial Crises*

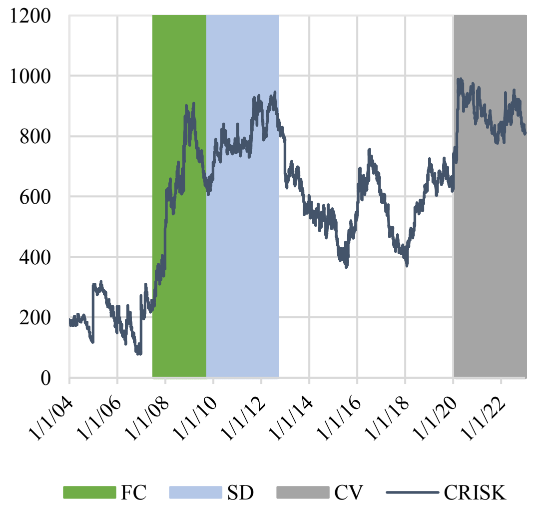
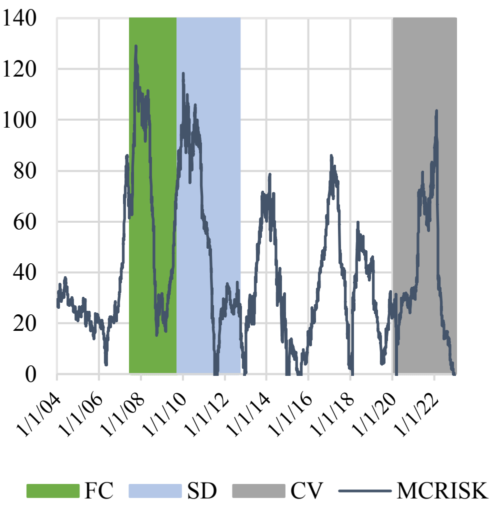


***Figure 12:** $\Sigma MCRISK$ in Financial Crises*



***FC** = Global Financial Crisis (July 2007- September 2009)*
***SD** = Sovereign Debt Crisis (October 2009 – August 2012)*
***CV** = COVID-19 Pandemic (February 2020 – December 2022)*
***CRISK**=* $\Sigma CRISK$ *in Billion Euros*
***MCRISK** =* $\Sigma MCRISK$ *in Billion Euros*
Source: Own illustration

For $\Sigma CRISK$, an increase is observed in the first shock period of each crisis, ranging from 0,1% in the sovereign debt crisis to 28,3% in the financial crisis. For the entire crisis period, a $\Sigma CRISK$ increased between 17,6% during the COVID-19 Pandemic and 158,7% during the Global Financial Crisis compared to pre-crisis levels.

An analysis of the pattern of $\Sigma MCRISK$ during financial crisis shocks yields ambiguous results. While $\Sigma MCRISK$ increased significantly in the first three-month shock periods, by 26,5% in the global financial crisis and by 21,6% in the sovereign debt crisis, a contrasting pattern is observed when analyzing the change of $\Sigma MCRISK$ over the entire crisis period. While $\Sigma MCRISK$ decreased by 0,8% during the financial crisis and by 21,8% during the sovereign debt crisis, it increased significantly by 62,5% in the Covid crisis.

A correlation analysis in Section 8.9 of the Appendix shows that the presence of the subprime debt crisis and the financial crisis has a significant positive correlation with $\Sigma CRISK$ and $\Sigma MCRISK$. In contrast, while the presence of the Covid crisis has a significantly positive correlation with $\Sigma CRISK$, it has a negative correlation with $\Sigma MCRISK$.

Detailed results and analyses of each financial crisis shock are available in Section 8.9.2 in the Appendix.

4.3.2. Cross-Sectional Evaluation of CRISK

This section examines the cross-sectional distribution of CRISK and MCRISK, analyzing patterns and concentrations by company, industry and country.

CRISK and MCRISK by Financial Institution

This section evaluates the concentrations of CRISK and MCRISK in different financial institutions. The average scores of CRISK and MCRISK for each institution over the observed period were calculated and used to rank the institutions according to their respective scores. The cumulative proportions of CRISK and MCRISK scores for successive institutions were subsequently determined.

Figure 13 and Figure 14 display the share of cumulative CRISK and MCRISK relative to the number of financial institutions. A steeper curve indicates a greater degree of concentration within particular companies. A grey reference line represents a hypothetical, entirely uniform distribution.

The initial steep slope of the CRISK and MCRISK curves suggests a high concentration of risk among a small subset of financial institutions. It is important to note that the CRISK curve exhibits a significant decline towards the end of the x-axis because 161 out of 237 companies have a negative average CRISK value. In contrast, this phenomenon is only observed in 29 out of 237 companies with MCRISK. Section 8.10.1 in the Appendix contains lists of the top ten companies with the highest average CRISK and MCRISK scores.

Concentration of CRISK

The results highlight a significant concentration of CRISK within individual financial institutions. On average, ten financial institutions, accounting for about 4,22% of all companies, accounted for 90,5% of the average $\Sigma CRISK$. One of the largest contributors to this concentration are companies such as BNP Paribas S.A. and Crédit Agricole S.A., which account for 16,6% and 16,3%, respectively, of the average a $\Sigma CRISK$.

When examining the share of average CRISK relative to average market capitalization of the observed institutions, there are still significant variations between companies. The highest average share is 1758,05%, represented by Crédit Agricole Alpes Provence, while the lowest positive share is 0,45%. This divergence in CRISK shares is also evident in the distribution shown in Figure 13, Panel 2.

Concentration of MCRISK

A similar concentration pattern emerges when evaluating MCRISK. In this context, ten financial institutions, accounting for about 4,22% of all companies, contributed to 66,7% of the average total $\Sigma MCRISK$. Banco Santander S.A. and BNP Paribas S.A. are the most significant contributors in this category, which contributed 12,5% and 10,5% of the average total $\Sigma MCRISK$.

In contrast, when analyzing the cumulative MCRISK in relation to the cumulative average market capitalization of the companies studied, only small variations are observed, which is also visually evident in Figure 14, Panel 2.

***Figure 13**: Cumulative Average CRISK*

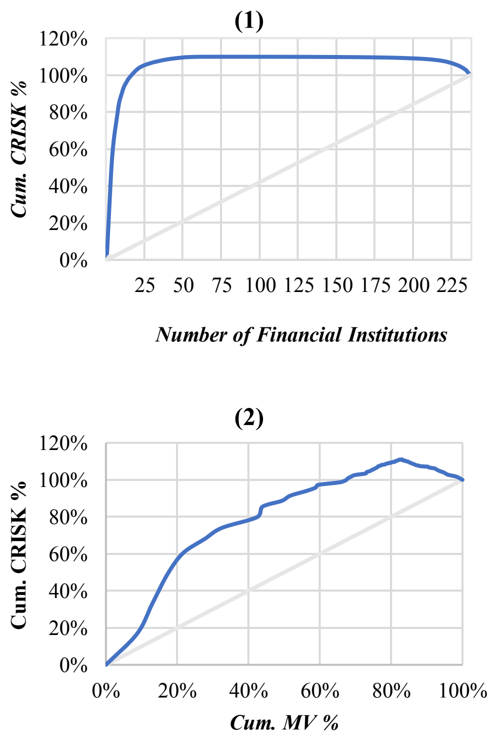
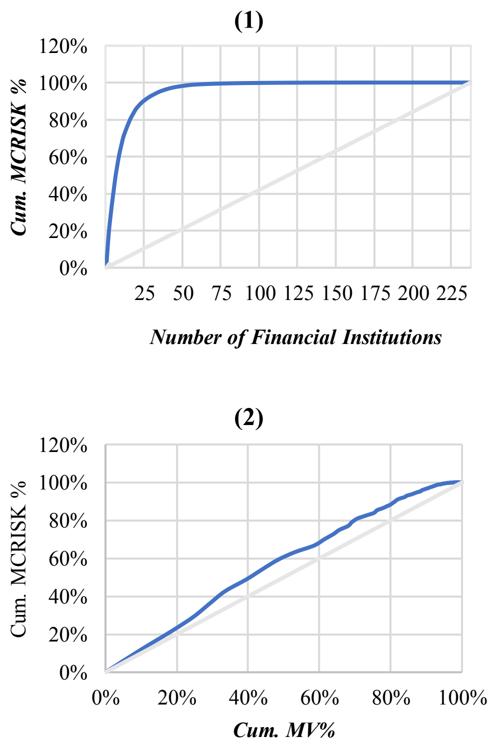


***Figure 14:** Cumulative Average MCRISK*



These graphs illustrate the cumulative average share of CRISK and MCRISK, respectively on the y-axis, relative to the number of financial institutions (1) and the share of cumulative average market capitalization (MV) (2), respectively, on the x-axis.

Source: Own illustration

Aggregate CRISK and MCRISK by Industry

This section examines $\Sigma CRISK$ and $\Sigma MCRISK$ for the two different GICS industries in the data sample, namely *Banks* and *Capital Markets*, and their respective sub-industries.[11]

Aggregate CRISK by Industry

Table 10 provides an overview of the summary statistics concerning the average aggregate CRISK within each industry and sub-industry over the observation period, revealing that the industry *Banks*, with an average $\Sigma CRISK$ of EUR 523,81 billion, contributes 88,1% to the average $\Sigma CRISK$ over the observation period. A closer examination shows that the *Diversified Banks* sub-industry has the most considerable impact within the Banks industry, accounting for 85,1% of the total $\Sigma CRISK$, which underscores its importance in the CRISK analysis.

During the observation period, both *Diversified* and *Regional Banks* show a consistently positive $\Sigma CRISK$, as shown by the minimum values. Remarkably, all sub-industries within the *Capital Markets* industry possess negative mean $\Sigma CRISK$ values, except for the Diversified Capital Markets sub-industry. This divergence can be partly ascribed to the inherent differences between the business models of *banks*, which includes borrowing money through deposits and other liabilities, and *financial services companies*, which mainly operate in the capital markets. This is one reason why banks have a considerably higher average debt-to-capital ratio, as demonstrated in Section 8.10.2 of the Appendix, which is a crucial driver that may significantly amplify $\Sigma CRISK$ in the banking industry.

Complementing this analysis, Section 8.10.2 in the Appendix, provides additional insights into $\Sigma CRISK$ trends over the observation period, broken down by industry and sub-industry, illustrating that, in addition to *Diversified Banks*, the *Diversified Capital Markets* sub-industry also significantly contributes to the overall $\Sigma CRISK$. Further, to examine the potential concentration of CRISK within specific sub-industries relative to MV, Table 34 in Section 8.9.2 in the Appendix shows the average ratio of $\Sigma CRISK$ for each sub-industry to average aggregate MV, revealing that these ratios vary significantly from -69,86% for *Investment Banking & Brokerage* to 479,39% for *Regional Banks.*

[11] Table 2 in Section 3.1.1 provides an overview of the observed industries and respective subindustries.

***Table 10:** Summary Statistics of Aggregate CRISK by Sub-Industry*

GICS Industry	GICS Subindustry	Mean	Median	Std. Dev.	Min.	Max.	31.12.22
Banks	*Diversified Banks*	510,06	544,42	224,90	46,30	928,48	757,96
	Regional Banks	13,75	13,72	5,53	4,65	25,84	25,73
	Total	523,81	557,74	229,55	52,70	949,66	783,69
Capital Markets	*Asset Mgmt. & Custody Banks*	-18,04	-10,91	14,20	-52,78	-2,50	-44,29
	Diversified Capital Markets	93,30	91,31	30,47	27,97	163,95	79,59
	Financial Exchanges & Data	-2,65	-3,63	7,97	-23,11	11,18	-2,38
	Investment Banking & Brokerage	-2,03	-1,23	1,99	-9,63	-0,59	-5,49
	Total	70,58	65,43	41,81	8,43	163,35	27,43
	Overall	**594,39**	**640,46**	**239,68**	**78,65**	**990,88**	**811,13**

This table shows the summary statistics of $\Sigma CRISK$ in billion euros.
***31.12.2022**= Value of $\Sigma CRISK$ in billion euros on 31.12.2022.*
Source: Own calculation

Aggregate MCRISK by Industry

Table 11 provides an overview of summary statistics for $\Sigma MCRISK$ by industry and sub-industry. Similar to the examination of $\Sigma CRISK$ distribution across industries, the *Diversified Banks* sub-industry accounts for 88,50% of the average $\Sigma MCRISK$, with a mean $\Sigma MCRISK$ of EUR 35,7 billion.

In contrast to the results related to CRISK, the analysis of the average $\Sigma MCRISK$ shows that there are no negative mean values in any sub-industries, showing that climate stress leads to an increase in the stressed $\Sigma CRISK$ values in all sub-industries compared to the non-stressed $\Sigma CRISK$ on average.

***Table 11:** Summary Statistics Aggregate MCRISK by Sub-Industry*

GICS Industry	*Subindustry*	Mean	Median	Std. Dev.	Min.	Max.	31.12.22
Banks	*Diversified Banks*	35,77	26,45	26,12	-10,95	117,17	-0,78
	Regional Banks	0,07	0,07	0,06	-0,04	0,22	0,01
	Total	35,84	26,55	26,14	-10,95	117,26	-0,77
Capital Markets	*Asset Management & Custody Banks*	1,04	0,98	0,68	-0,36	3,75	-0,34
	Diversified Capital Markets	2,82	2,34	1,96	-0,17	9,06	-0,16
	Financial Exchanges & Data	0,67	0,69	1,39	-4,48	5,74	-1,67
	Investment Banking & Brokerage	0,04	0,05	0,10	-0,54	0,26	0,03
	Total	4,57	3,96	3,02	-2,17	13,01	-2.14
Overall		**40,42**	**30,44**	**28,48**	**-8,35**	**129,18**	**-2,91**

This table displays the summary statistics of $\Sigma MCRISK$ in billion euros.
***31.12.2022**= Value of $\Sigma MCRISK$ in billion euros on 31.12.2022.*
Source: Own calculation

Figure 31 in Section 8.10.2 in the Appendix visually represents the evolution of $\Sigma MCRISK$ values over time within different sub-industries during the observation period.

To further examine the potential concentration of $\Sigma MCRISK$ within specific subindustries relative to market capitalization, Table 35 in Section 8.10.2 in the Appendix shows the average ratio of $\Sigma MCRISK$ for each sub-industry to average aggregate market capitalization. The results show that these ratios vary from 0,68% (for *Regional Banks*) to 9,14% (for *Diversified Capital Markets*) but do not reveal any significant concentration of MCRISK within any particular subindustry. The evolution of this ratio over time is available in Section 8.10.2 of the Appendix.

Aggregate CRISK and MCRISK by Country

Aggregate CRISK by Country

Table 12 shows the summary statistics of $\Sigma CRISK$ by country, with countries sorted by the descending mean of $\Sigma CRISK$ values.

The results show that $\Sigma CRISK$ differs significantly across the observed countries, with five countries contributing 94,99% to the total $\Sigma CRISK$ in the Eurozone throughout the observation period on average. Of particular note is France, which has a significantly higher $\Sigma CRISK$ compared to the other countries, accounting for 45,39% of the total $\Sigma CRISK$ on average. Notably, the $\Sigma CRISK$ of all other eurozone countries combined is equal to or lower than the $\Sigma CRISK$ of one of the top five countries with the highest $\Sigma CRISK$. Six countries in the dataset even have a slightly negative average $\Sigma CRISK$.

One factor contributing to the high $\Sigma CRISK$ values in the top five countries with the highest $\Sigma CRISK$ is the aggregate market value of equity of the financial institutions in these countries, which, on average, contributes 77,14% to the total MV.

However, if the aggregate market size of the financial institutions in each country is taken into account by evaluating the ratio between average $\Sigma CRISK$ and average aggregate market capitalization, the two countries with the highest average $\Sigma CRISK$, France and Germany, also have the highest ratio between average $\Sigma CRISK$ and average aggregate market capitalization, 227,62%, and 205,22%, respectively. The other countries, on the other hand, show a considerable range, with Estonia having the lowest ratio at -83,32%.

This analysis underscores the significant variation in $\Sigma CRISK$ across diverse nations and further suggests that CRISK is highly concentrated in the top five countries, bearing a substantial share of the financial risk within the Eurozone.

***Table 12:** Summary Statistics of Aggregate CRISK by Country*

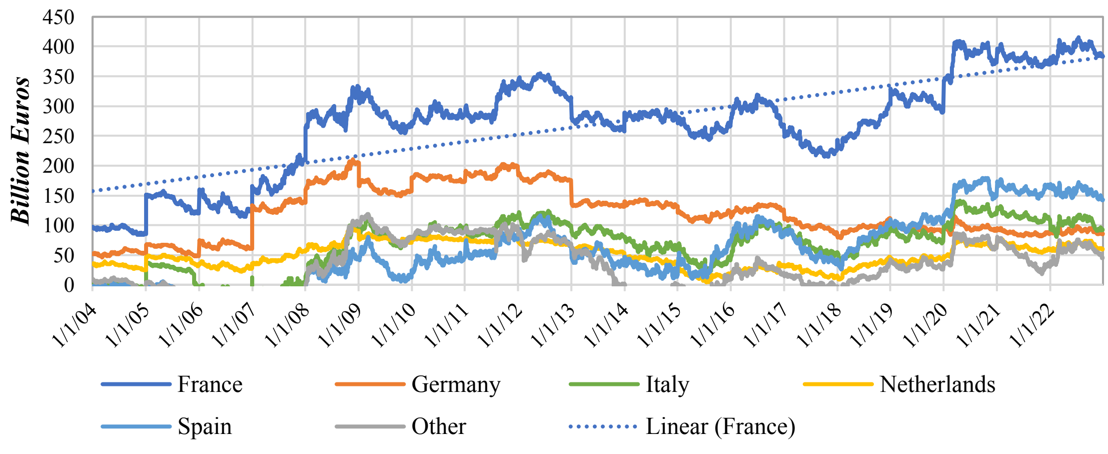
	Mean	**Median**	**Std. Dev.**	**Min.**	**Max.**	**31/12/2022**	**%CRISK**	**%MV**
France	269,77	282,37	82,67	83,57	416,11	384,53	45,38%	227,62%
Germany	120,02	114,84	42,31	45,86	210,08	85,78	20,19%	205,22%
Italy	66,88	79,51	41,68	-26,61	140,83	92,37	11,25%	82,74%
Spain	57,79	49,42	58,23	-51,82	179,63	143,05	9,72%	51,78%
Netherlands	50,19	47,52	20,82	4,50	93,97	60,09	8,44%	144,19%
Finland	15,23	15,56	8,60	-1,35	38,15	10,42	2,56%	51,44%
Austria	10,02	10,48	7,68	-10,06	27,74	21,67	1,69%	55,15%
Greece	5,19	9,17	12,49	-26,58	24,16	7,29	0,87%	138,35%
Portugal	2,47	2,95	2,56	-7,12	6,33	4,46	0,42%	141,45%
Belgium	1,59	0,08	8,33	-13,7	22,16	2,46	0,27%	35,12%
Ireland	0,83	-0,31	19,69	-75,66	32,54	4,72	0,14%	178,60%
Slovakia	0,44	0,33	0,44	-0,18	1,62	1,53	0,07%	41,06%
Slovenia	0,07	0,00	0,19	-0,26	0,76	0,57	0,01%	101,54%
Lithuania	-0,02	0,00	0,05	-0,17	0,07	-0,08	0,00%	1,13%
Estonia	-0,07	0,00	0,19	-0,97	0,14	-0,62	-0,01%	-55,42%
Cyprus	-0,40	0,09	2,29	-15,89	2,15	1,66	-0,07%	-45,03%
Croatia	-0,71	-0,50	0,92	-4,87	0,29	-0,57	-0,12%	-25,13%
Malta	-1,18	-1,08	1,17	-5,20	0,70	0,43	-0,20%	-32,96%
Luxembourg	-3,70	-3,39	2,78	-10,28	-0,20	-8,62	-0,62%	-83,32%
Overall	**594,39**	**640,46**	**239,68**	**78,65**	**990,88**	**811,13**	**100%**	**107,77%**

This table displays the average $\Sigma CRISK$ by country in billion euros, sorted descending by the highest average $\Sigma CRISK$
***31/12/22:** Indicates the $\Sigma CRISK$ per country as of December 31st 2022*
***%CRISK:** Indicates share the $\Sigma CRISK$ per country contributes to total $\Sigma CRISK$*
***%MV:** Indicates the average ratio of $\Sigma CRISK$ to ΣMV*
Source: Own calculation

Figure 15 illustrates the time series development of the $\Sigma CRISK$ during the observation period of the five countries with the highest average $\Sigma CRISK$ values, showcasing a significant increase in $\Sigma CRISK$, specifically in France.

Moreover, a supplementary analysis in Section 8.10.3 of the Appendix provides insights into the time series development of $\Sigma CRISK$ in all observed countries, as well as the distribution of $\Sigma CRISK$ among the top three observed financial institutions based on market capitalization within the top five countries ranked by mean $\Sigma CRISK$. This additional analysis reveals that CRISK is concentrated on a select few companies, indicating the presence of significant risk exposure within a limited subset of financial institutions. Further, this supplementary analysis also provides an overview of the development of $\Sigma CRISK$ relative to the aggregate MV per country.

Figure 15: *Aggregate CRISK by Country*



The values are truncated at zero.

Source: Own creation

Aggregate MCRISK by Country

Table 13 shows the summary statistics of $\Sigma MCRISK$ by country, ranked in descending order based on the mean $\Sigma MCRISK$ by country. As shown in the table, Spain, France, Italy, Germany, and the Netherlands are the five countries that contribute most to $\Sigma MCRISK$, with an average aggregate share of 75,48% of total $\Sigma MCRISK$ over the observation period.

In contrast to the $\Sigma CRISK$ analysis by country, Spain has the highest average $\Sigma MCRISK$, contributing an average of 22,14% to the total $\Sigma MCRISK$. The analysis shows that although the MCRISK is still concentrated in the same five countries, the concentration less pronounced than in the CRISK analysis.

In addition, the table shows the ratios of the average $\Sigma MCRISK$ to the average aggregate market capitalization, which range from 0,11% to 9,41%, where Finland has the highest ratio. It is worth noting that there are no significant differences between the countries or significant outliers, with a standard deviation of the ratio of 2,82%.

Figure 36 in Section 8.10.3 in the Appendix further shows the time evolution of the $\Sigma MCRISK$ of the five countries with the highest average $\Sigma MCRISK$. This illustration shows that the pattern of sharp peaks at specific dates, previously observed in the overall $\Sigma MCRISK$, is also observed at the individual country level, particularly in the five countries with the highest $\Sigma MCRISK$. Further, a supplementary analysis in Section 8.10.3 provides an overview of the development of $\Sigma MCRISK$ relative to the aggregate market capitalization per country.

Table 13: *Summary Statistics of Marginal CRISK by Country*

	Mean	Median	Std. Dev.	Min.	Max.	31/12/2022	%CRISK	%MV
Spain	8,950	7,026	7,354	-6,890	31,989	-0,089	22,14%	6,64%
France	8,935	7,338	6,499	-4,516	27,296	-0,199	22,11%	6,84%
Italy	4,581	3,185	5,419	-5,914	23,088	0,031	11,33%	4,34%
Germany	4,453	3,780	3,312	-1,891	14,342	-0,022	11,02%	7,22%
Netherlands	3,589	3,021	2,486	-1,499	11,821	-0,005	8,88%	8,19%
Finland	3,066	2,834	1,605	-0,258	7,523	0,550	7,59%	9,41%
Austria	1,768	1,477	1,404	-0,447	6,794	-0,032	4,37%	7,65%
Belgium	1,758	1,464	1,459	-0,560	7,743	-1,869	4,35%	7,54%
Greece	1,559	0,763	2,001	-0,724	9,280	-0,092	3,86%	6,93%
Ireland	1,115	0,562	2,313	-11,889	11,569	0,039	2,76%	5,91%
Portugal	0,195	0,156	0,244	-0,420	1,280	-1,819	0,48%	5,25%
Malta	0,146	0,072	0,152	-0,016	0,664	-0,003	0,36%	4,22%
Luxembourg	0,130	0,119	0,133	-0,397	0,449	0,088	0,32%	3,54%
Cyprus	0,100	0,042	0,186	-0,121	1,206	0,022	0,25%	5,30%
Croatia	0,055	0,043	0,116	-0,417	0,448	1,149	0,14%	2,85%
Slovenia	0,007	0,000	0,023	-0,028	0,129	0,016	0,02%	0,11%
Lithuania	0,005	0,003	0,007	-0,017	0,027	0,002	0,01%	4,36%
Estonia	0,003	0,000	0,008	-0,042	0,059	0,025	0,01%	4,74%
Slovakia	0,003	0,003	0,017	-0,069	0,053	-0,699	0,01%	0,55%
Overall	**40,42**	**30,439**	**28,481**	**-8,352**	**129,179**	**-2,907**	**100%**	**6,62%**

This table displays the average $\Sigma MCRISK$ by country in billion euros, sorted descending by the highest average $\Sigma MCRISK$
31/12/.22: *Indicates the $\Sigma MCRISK$ per country as of December 31st 2022*
%CRISK: *Indicates share the $\Sigma MCRISK$ per country contributes to total $\Sigma MCRISK$*
%MV: *Indicates the average ratio of $\Sigma MCRISK$ to ΣMV*
Source: Own calculation

4.4. Extensions

This section presents two extensions of the analysis, one focusing on an event study analyzing the impact of transition risk events on Stranded Asset Portfolio Returns and one focusing on the impact of natural disasters on $\Sigma MCRISK$.

4.4.1. Event Study of Exogenous Climate Policy Shocks on Climate Beta

The objective of this event study is to examine the impact of exogenous climate policy shocks on the stock returns of the Stranded Asset Portfolio and to empirically validate whether transition risk events are interrelated with a significant change in $r_{CF_{Str},t}$. A similar event study has been employed by Kruse et al. (2020), who examined the impact of adopting the Paris Agreement as an exogenous shock on stock returns of US-American companies.

The timeline for the examined policy shocks was obtained from the European Parliament (2022) and was supplemented by additional events related to climate change transition risk.

To assess the impact of exogenous shocks on the return of the Stranded Asset Portfolio, an event study method is following the market model approach of Brown & Warner (1985), where the *abnormal return AR* and the *cumulative abnormal return CAR* are calculated using an OLS Market Model. A detailed methodology of estimation of *AR* and *CAR* with the OLS market model approach is available in the Appendix in Section 8.12. During the estimation window, which spans from *t= -365* days before the event date to *t=-31* days, the expected daily return $E(r_{CF_{Str},t})$ of the Stranded Asset Portfolio is estimated. Next, in the event window spanning from t-30 days before the event to t+30 days after the event, $AR_{CF(Str),t}$ and $CAR(t_0, T)$ are calculated as:

(16)
$$AR_{CF(Str),t} = r_{CF_{Str},t} - E(r_{CF_{Str},t}) = r_{CF_{Str},t} - (\hat{\alpha} + \hat{\beta} \times r_{MKT,t})$$

(17)
$$CAR(t_0, T) = \sum_{t=t_0}^{T} AR_{CF(Str),t}$$

Source: Brown & Warner (1985)

$CAR(t_0, T)$ is calculated for three different event window sizes:

1. $CAR(t_{-30}, t_{30})$: Includes the entire event window, from 30 days before the event to 30 days after the event, with the aim to explore potential market expectations and trends related to the event.
2. $CAR(t_0, t_7)$: In this scenario, the analysis focuses on immediate market reactions and short-term effects by examining the event window from the event date to seven days after the event (T+7).

3. $CAR(t_0, t_{30})$: This calculation focuses on the medium-term abnormal return by analyzing the event window from the event date to 30 days after the event.

To evaluate the statistical significance of $AR_{CF(Str),t}$ and $CAR(t_0, T)$, two t-tests are performed: The first test examines the null hypothesis that the average abnormal return in the event window $\overline{AR}(t_0, t_{30})$ is equal to zero (H0: $\overline{AR}$ = 0), assuming a normal distribution, following the approach proposed by Brown & Warner (1985).

The second test examines the null hypothesis that the *CAR* is zero (H0: CAR = 0). This hypothesis is tested for $CAR(t_{-30}, t_{30})$, $CAR(t_0, t_7)$, and $CAR(t_0, t_{30})$, assuming a normal distribution.

The results of the analysis are presented in Table 14 and indicate that transition-related climate change events partly have a significant effect on the *CAR* of the Stranded Asset Portfolio. Further, Figure 38 in Section 8.12 of the Appendix illustrates the cumulative abnormal returns for all observed events.

Events with an increase of $r_{CF_{Str},t}$

The election of Donald Trump as U.S. President on 08/11/2016 was interrelated with a statistically significant increase in the stranded assets portfolio with a $CAR(t_0, t_{30})$ of 6,51%. Similarly, the Russian invasion of Ukraine on February 24th, 2022, showed a statistically significant increase in the portfolio of stranded assets with a $CAR(t_0, t_{30})$ of 10,36%. One possible explanation could be that the invasion was interrelated with an energy crisis.

Events with a decrease of $r_{CF_{Str},t}$

In contrast, the observed events involving policy decisions aimed at mitigating the negative impacts of climate change, result in a negative CAR for the most part. However, it is essential to emphasize that the significance of the outcomes of these events varies. For example, the adoption of the Paris Agreement showed a statistically significant negative $CAR(t_0, t_{30})$ of -2,77%, while the adoption of the Glasgow Climate Pact was interrelated with a statistically significant $CAR(t_0, t_{30})$ of -4,50%.

Interestingly, the declaration of climate emergency by the European Parliament on November 28th 2019 led to ambiguous results. While the short-term $CAR(t_0, t_7)$ was negative at -0,99%, other measured event windows showed a positive CAR. One explanation for this could be that other factors may have significantly affected the return of the Stranded Asset Portfolio during this period.

***Table 14:** Event Study Results – AR and CAR*

Date	Event Description	Effect on Stranded Asset Portfolio				
		$\overline{AR}_{0,30}$	$CAR_{-30,30}$	$CAR_{0,7}$	$CAR_{0,30}$	*Expected*
12/12/2015	Paris Agreement is adopted (UNFCCC, 2023)	-0,13%	-9,67%***	-0,25%	-2,77%**	-
08/11/2016	Donald Trump is elected as US president (Statista, 2016)	+0,28%	+4,45%***	+1,96%**	6,51%***	+
28/11/2019	European Parliament declares climate emergency	+0,12%	+2,12%***	-0,99%**	+2,66%***	-
07/10/2020	European Parliament votes to approve European Climate Law on Climate Neutrality by 2050 (European Parliament, 2020)	-0,09%	-1,90%	-0,46%**	-1,93%	-
08/07/2021	ECB presents action plan how to include climate change in its monetary policy strategy (European Central Bank, 2021)	-0,14%	-3,16%***	-1,48%**	-3,17%***	-
29/07/2021	European Climate Law is adopted by European Council (European Commission, 2021)	-0,04%	-4,71%	-0,81%**	-0,92%***	-
13/11/2021	COP26 adopts Glasgow Climate Pact (United Nations, 2021)	-0,21%	-8,63%	-3,04%	-4,50%***	-
24/02/2022	Russia starts invasion in Ukraine (Statista, 2023a)	+0,47%	+18,33%**	+11,08% **	+10,36%***	+

*Significance levels: *** p<0.01, ** p<0.05, * p<0.1*

***Source:** Own illustration*

In evaluating these results, certain limitations must be considered. First, there may be event selection bias because the study focuses on a limited number of events, precluding the generalizability of the results to all climate change-related events.

Second, it is crucial to question the strength of the observed events as the sole cause of the observed CARs. Additionally, the choice of estimation period, the size of the event window, and the underlying model could affect the results and, therefore, should be treated with prudence.

Finally, it is critical to consider the potential impact of external factors beyond the singular event under study that may have affected stock returns and made it difficult to isolate the specific impact of the event. Therefore, further research should aim to control for additional external factors that could potentially affect the CAR to enhance the robustness of the analysis.

4.4.2. MCRISK and Natural Disasters

This section investigates whether there is a relationship between the $\Sigma MCRISK$ of the observed financial institutions and the occurrence of economic losses associated with natural disasters in the Eurozone within the observed period. The rationale for this investigation is that studies suggest that acute physical risk, such as in natural disasters, can amplify transition risk since there may be a sudden change in climate policy as a reaction to natural disasters. As the frequency and intensity of natural disasters increase, they may trigger a chain reaction that culminates in the anticipation of more stringent climate policies (Daumas, 2023). This shift creates transition risk, which may reduce the returns of the Stranded Asset Portfolio and increase $\Sigma MCRISK$.

Consequently, this section aims to identify possible correlations and implications of this relationship between natural disasters, climate policies, transition risks, and $\Sigma MCRISK$, by testing the hypothesis that the $\Sigma MCRISK$ increases in years with higher economic costs caused by natural disasters.

To test this hypothesis, data on natural disasters in the observed Eurozone countries during the observation period is obtained from the EM-DAT disaster database from the Centre for Research on the Epidemiology of Disasters (CRED). This dataset contains information on economic losses caused by natural disasters in USD per country (Centre for Research on the Epidemiology of Disasters (CRED), 2023).

Based on this data, annual economic losses in USD ($Loss_{i,t}$) are calculated for each country *i* in the Eurozone for each year *t* over the observation period. In addition, the $GDP_{i,t}$ per country *i* per year *t* in USD is retrieved from the World Bank database to calculate the variable $DMG_{i,t}$, representing the total annual damage from natural disasters as a share of GDP for each country (The World Bank, 2023)

Based on this data, the variable DMG, representing the annual economic losses caused by natural in USD per country *i* relative to the annual GDP per country in USD, is calculated:

(18)
$$DMG_{i,t} = \frac{Loss_{i,t}}{GDP_{i,t}}$$

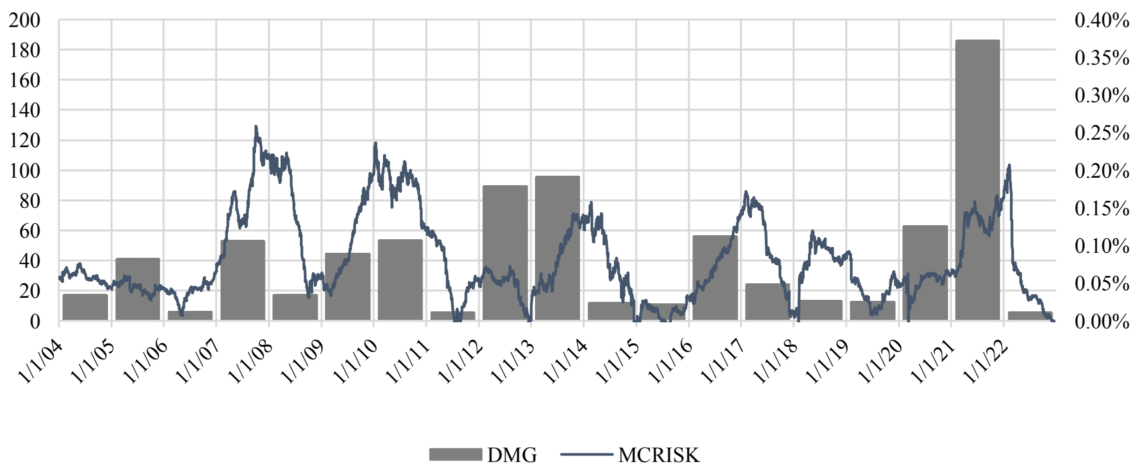
Further, the aggregate DMG (DMG_t) for all *n* countries is calculated and presented in Figure 16.

(19)
$$DMG_t = \sum_{i=1}^{n} DMG_{i,t} = \frac{\sum_{i=1}^{n} Loss_{i,t}}{\sum_{i=1}^{n} GDP_{i,t}}$$

A correlation analysis shows that DMG_t and the annual average $\Sigma MCRISK_t$ have a correlation coefficient of 0,316. An OLS regression is subsequently performed with DMG_tas the independent variable and $\Sigma MCRISK_t$ as the dependent variable.

The regression results show a positive coefficient for DMG, which means that a higher proportion of total damage is associated with a higher $\Sigma MCRISK_t$ score. However, this coefficient is not statistically significant as the calculated p-value is 0,188.[12] Therefore, the initial hypothesis cannot be confirmed based on the presented analysis.
For future research, it might be interesting to perform the analysis at a more granular level to further investigate the relationship between the two variables. For example, analyzing monthly DMG data or examining each country individually could provide more insight and possibly reveal statistically significant relationships between $\Sigma MCRISK$ and the occurrence of economic losses due to natural disasters.

Figure 16: *Share of Economic Damages Caused by Natural Disasters of GDP*



This figure shows the aggregated $\Sigma MCRISK_t$ in the Eurozone in billion euros on the left y-axis. Further, it shows DMG_t, the annual average share of economic damages caused by natural disasters in the Eurozone as a share of the annual GDP per country on the right y-axis.
Source: Own illustration

[12] The regression analysis is available in the Appendix in Section 8.11.

4.5. Sensitivity Analysis

In the previous results section, the analysis was conducted using a hypothetical climate stress level of a 50% decrease in returns of the Stranded Asset Portfolio over six months. This section aims to assess the sensitivity of $\Sigma CRISK$ and $\Sigma MCRISK$ to alternative stress levels, spanning from 25% to 90%.

Table 18 presents the mean and maximum $\Sigma CRISK$ and $\Sigma MCRISK$ depending on the alternative stress scenarios. It can be observed that $\Sigma CRISK$ shows only minor variability in response to changes in the climate stress scenarios. For example, a shift in stress level from 25% to 75% leads to an increase in mean $\Sigma CRISK$ of only 5,9%. Similarly, a reduction to 25% leads to a slight decrease of 3,9% compared to the baseline stress level of 50%.

In contrast, $\Sigma MCRISK$ values show significantly greater variability between stress scenarios. In particular, an increase in climate stress to 75% leads to an 87,2% increase in the mean $\Sigma MCRISK$ value.

The pronounced variance of $\Sigma MCRISK$ compared to $\Sigma CRISK$ may result from the fact that while $\Sigma CRISK$ also depends on the level of market value of equity and book value of debt, $\Sigma MCRISK$ isolates the sensitivity to Climate Beta and climate stress.

Table 15: *Aggregate CRISK and MCRISK in Climate Stress Scenarios (Billion Euros)*

Stress Level		25%	50%	75%	90%
$\Sigma CRISK$	**Mean**	571,43	594,39	629,66	669,59
	Δ to θ =50%	*-3,9%*	*0,0%*	*5,9%*	*12,7%*
	Max	984,64	990,88	1004,98	1029,10
	Δ to θ =50%	*-0,6%*	*0,0%*	*1,4%*	*3,9%*
$\Sigma MCRISK$	**Mean**	17,45	40,42	75,68	115,61
	Δ to θ =50%	*-56,8%*	*0,0%*	*87,2%*	*186,0%*
	Max	56,26	129,18	238,42	357,55
	Δ to θ =50%	*-56,4%*	*0,0%*	*84,6%*	*176,8%*

This table shows $\Sigma CRISK$ and $\Sigma MCRISK$ values in billion euros and the percent change of $\Sigma CRISK$ and $\Sigma MCRISK$ depending on the stress scenario θ compared to the baseline stress scenario θ =50% in italic.

Source: Own calculation

Figure 17 illustrates the time trend of $\Sigma MCRISK$ as a function of different stress levels.

To further explore the sensitivity of $\Sigma MCRISK$, Figure 18 shows the average $\Sigma MCRISK$ value at stress levels between 0% and 99%. The pattern of an increase in $\Sigma MCRISK$ in relation to stress level is not linear but follows an exponential curve. While small increases in the average $\Sigma MCRISK$ score result from an increase in stress level from a low starting level, significant increases are seen when an already high stress level is increased. In particular, the figure illustrates that the average $\Sigma MCRISK$ becomes slightly negative when the stress level is below 12%. This phenomenon can be attributed to the non-linear relationship between the stress level in the formula used to calculate $\Sigma MCRISK$ and $\Sigma CRISK$.

Figure 17: *Sensitivity of Aggregate MCRISK to Climate Stress Scenarios*

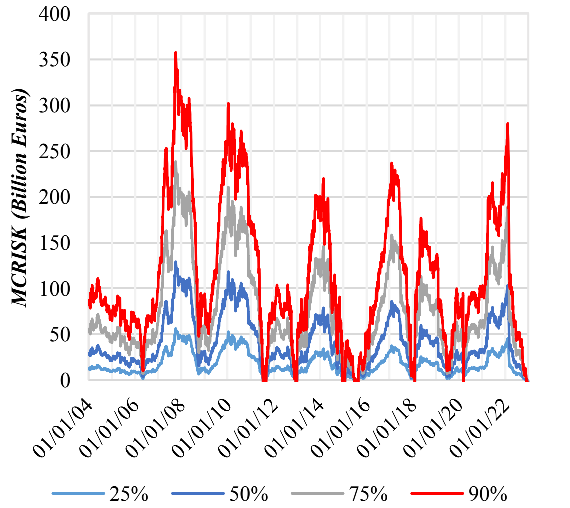
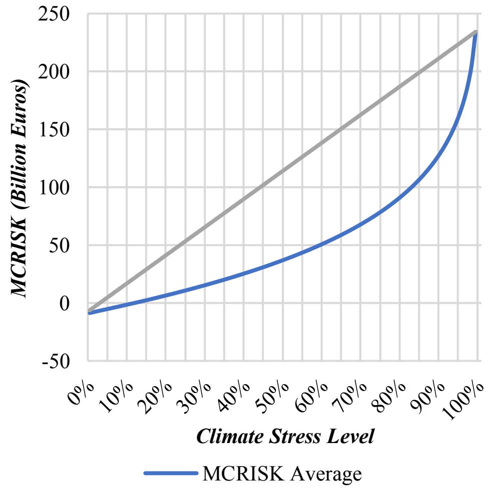


Figure 18: *Sensitivity Average MCRISK to Climate Stress*



Source: Own Illustration

5. Discussion

This section addresses the previously defined research questions and discusses the implications arising from the findings. Further, the limitations of the study and possible avenues for future research are discussed.

5.1. Evaluation of Research Questions and Implications

In this section, the primary research question "*How does climate-related transition risk impact financial institutions and systemic risk within the Eurozone, and what are the dynamic trends, and concentration patterns associated with climate-related risks?*" is assessed by first answering the sub-questions and finally combining all findings to answer the primary research question.

Research Question 1.1: *How does the average Climate Beta of the financial institutions in the data sample develop over the observation period?*

The results indicate a positive *fixed Climate Beta* of 0,103 across the entire data sample. This value indicates a positive sensitivity of financial institutions to the Stranded Asset Portfolio and, thus, to transition risk.

Furthermore, a positive average *time-varying Climate Beta* is obtained using the rolling window regression with a mean value of 0,118.

One possible explanation provided by Jung et al. (2023) for the low values of Climate Betas is the potentially nonlinear relationship between the sensitivity of the returns of financial institutions and the Stranded Asset Portfolio, namely that the returns on the shares of financial institutions are expected to be relatively insensitive to changes in the returns of fossil fuel companies if they are reasonably far from default.

When *examining temporal differences*, the average Climate Beta remains constantly positive throughout the observation period until December 2022. Overall, the average Climate Beta within the Eurozone shows a range from -0,0038 to 0,3191. These considerable variations underline the importance of estimating Climate Beta dynamically for the calculation of CRISK and are in line with the principles recommended by Jung et al. (2023). Despite the observed fluctuations, the analysis does not indicate an increasing trend in Climate Beta over time.

In summary, the results highlight that, on average, financial institutions in the Eurozone have a positive sensitivity to transition risk when applying the Stranded Asset Portfolio as a proxy for transition risk. This observation underscores the need for financial institutions to actively manage their exposure to transition risks.

Research Question 1.2: *Do the financial institutions in the data sample exhibit a positive aggregate CRISK and MCRISK, and how does the aggregate CRISK and MCRISK of the financial institutions in the data sample change over the observation period?*

Over the observation period, the mean aggregate CRISK is EUR 594,39 billion, with a minimum value of EUR 78,65 billion euros, indicating that the *$\Sigma CRISK$ of the financial institutions is consistently positive over the entire observation period*. $\Sigma CRISK$ can be interpreted as the aggregate capital shortfall of financial institutions, and thus, the capital injection required by the financial system in times of the defined stress scenario. A positive $\Sigma CRISK$ may arise either because of an undercapitalization of companies or because of a positive aggregate MCRISK, underlining the systemic risk of transition risk.

In addition to the $\Sigma CRISK$, the analysis also finds a positive average $\Sigma MCRISK$ of EUR 40,42 billion on average over the observation period. Moreover, the difference of the $\Sigma CRISK$ in a stressed scenario compared to a non-stressed scenario is statistically significant from zero at a 1% significance level. This dynamic implies that systemic risk increases in stressed scenarios where six-month returns on the Stranded Asset Portfolio decrease by 50% compared to non-stressed scenarios. This result means that exposure to transition risk through the stress scenario contributes, on average, to an increased expected capital shortfall.

Looking at the *time-series development of CRISK and MCRISK*, different patterns emerge over the observation period.

For $\Sigma CRISK$, a statistically significant upward slope with a positive trend line of 0,074 can be observed, indicating a growing risk potential within financial institutions over time.

For the $\Sigma MCRISK$, on the other hand, the situation is different. An OLS regression shows a decreasing trend over the observation period, with a slope of -0,0017. However, it is important to note that the R-squared value in this case is very low, indicating limited explanatory power for this particular trend.

In summary, the analysis finds a positive $\Sigma CRISK$ and $\Sigma MCRISK$ over the observation period, implying that the observed stress scenario would cause systemic risk to the financial system.

Research Question 1.3: *Are CRISK and MCRISK concentrated in specific companies, industries, or countries within the data sample?*

The results show patterns of concentration of CRISK and MCRISK in companies, sub-industries and countries:

First, CRISK and MCRISK show *significant concentration within specific geographic regions*. 94,99% of the average CRISK aggregate is concentrated in just five out of twenty countries. Similarly, 75,48% of MCRISK is concentrated in five countries.

This concentration also extends to subindustries of financial institutions. In particular, MCRISK is *highly concentrated in banks*, with about 88,67% of MCRISK in the banking sector, and within this sector, about 88,5% of MCRISK in the diversified banks sub-sector.

Furthermore, the results of the analysis show the concentration of CRISK and MCRISK within certain companies. On average, *90,50% of CRISK can be attributed to only ten financial institutions*, and 66,70% of MCRISK is associated with the same number of financial institutions.

In addition, the considerable variations in the ratio of CRISK and MCRISK to market capitalization between companies can pose a significant climate risk even in some smaller companies. Even if the absolute value of CRISK and MCRISK is not as large for smaller companies and thus does not pose a systemic risk, a high value in relation to market capitalization can pose a significant risk to the company itself.

The observed concentrations and heterogeneity across different firms, industries and countries imply that regulatory efforts should focus on the most vulnerable firms to mitigate systemic risk.

Research Question 1.4: _How do CRISK and MCRISK of financial institutions in the dataset evolve in times of economic recessions and in response to exogenous shocks such as the onset of financial crises, climate policy shifts, and increased economic losses due to natural disasters?_

During the analyzed recessions, both $\Sigma CRISK$ and $\Sigma MCRISK$ increase significantly. $\Sigma CRISK$ increases by 24,01% in recession times compared to non-recession times and has a statistically significant positive correlation with the presence of a recession. $\Sigma MCRISK$ also shows a substantial increase of 25,34% in recession periods compared to non-recession periods, with a statistically significant positive correlation with the presence of a recession. This indicates an amplification of climate stress during market stress.

During the observed financial crises, $\Sigma CRISK$ increased between 0,1% and 28,3% in the first three months after the shock that marks the onset of the crisis and between 17,6% and 158,7% over the entire crisis period compared to the month before the crisis. This development can be attributed, among other things, to the decline in the market value of equity E_{it}, which ceteris paribus leads to a decline in the CRISK. In fact, the financial crisis shocks led to a decrease in the total market value of equity E_{it} between 7,3% and 35,1% compared to the average value in the month before the shock.

However, the results regarding the financial crises for $\Sigma MCRISK$ are mixed and vary depending on the crisis analyzed. For example, $\Sigma MCRISK$ decreased by 18,3% during the first shock period of the COVID-19 pandemic. This counterintuitive behavior cannot be explained by a lower beta alone, as the average $\beta_{it}^{Climate}$ increased significantly by 63,8%. Further research would be needed to understand the reasons for this discrepancy.

Despite the ambiguous results for $\Sigma MCRISK$, the analysis shows a positive correlation between $\Sigma CRISK$ and $\Sigma MCRISK$ and the presence of financial crises, except in the case of the COVID-19 crisis, where the correlation is positive for $\Sigma CRISK$ but negative for $\Sigma MCRISK$.

These results highlight the importance of risk regulation of financial institutions concerning climate risk, especially in times of recession and financial crisis to preserve financial stability.

The event study analysis of the impact of external transition-related climate shocks on the Stranded Asset Portfolio $CF_{Str,t}$ returns revealed that positive policy shocks, indicating a tightening of climate regulation, predominantly led to negative abnormal returns. Conversely, negative policy shocks signaling a loosening of climate regulation lead to a positive abnormal return. However, the significance of these results varies, and it is crucial to consider the limitation of possible event selection bias.

Furthermore, it was investigated whether $\Sigma MCRISK$ captures the impact of physical risk shocks. A regression of the share of annual economic losses from natural disasters relative to total GDP in the Eurozone against the average annual total $\Sigma MCRISK$ shows a positive association, although not a significant one. Therefore, it cannot be unequivocally concluded that the physical shocks from economic damages from natural disasters have a significant impact on the $\Sigma MCRISK$ of the financial institutions studied.

In conclusion, the sub-questions show that there is significant systemic climate-related transition risk for financial institutions, as implied by the positive average $\Sigma CRISK$, with an increasing trend over the observation period.

A positive average $\Sigma MCRISK$ further implies that the exposure of financial institutions to transition risk through the stress scenario contributes, on average, to an increased expected capital shortfall. Although there is no upward trend, supplementary analysis has shown that $\Sigma MCRISK$ can increase significantly during periods of financial stress, such as recessions. CRISK and MCRISK are also highly concentrated in specific companies, industries, and regions.

5.2. Limitations and Future Research Opportunities

Limitations

With regards to the dataset, one of the limitations of the analysis is the assumption of a synthetic Eurozone over the observation period to mitigate survivorship bias. In reality, however, it is important to recognize that some countries adopted the euro currency only after the start of the observation period. The applicability of the results to the broader Eurozone context may be affected by this limitation.

Another limitation results from the exclusive focus on listed financial institutions. This approach unavoidably omits data from non-listed institutions, possibly introducing bias into the overall analysis.

In addition, the data availability for all variables over the entire observation period is limited for some of the observed firms. This data incompleteness may introduce bias and consequently affect the overall robustness of the study's conclusions.

Another notable limitation concerns the approximation of total bank debt using the liabilities variable to account for customer deposits. This approximation, necessitated by the limited data availability on deposits of the financial institutions, may introduce inaccuracies in the assessment of the actual total bank debt and consequently affect the overall results.

Focusing on limitations in the methodology, one limitation is that the analysis focuses exclusively on transition risk and relies solely on the Stranded Asset Portfolio as a proxy of transition risk. Further, the analysis only focuses on historical transition risk shock scenarios. Additionally, the R squared of the regressions to estimate the Climate Beta is relatively low, implying that there are additional factors apart from the observed independent variables that may have caused the variability of returns of the financial institutions.

Future Research Opportunities

For future research, exploring the impact of a compound risk scenario where both the Stranded Asset Portfolio and the Market Portfolio experience simultaneous declines, as applied by Jung et al. (2023), could provide valuable insights. In addition, a focused assessment of Climate Beta based solely on the returns of companies within the banking GICS sector could provide more nuanced perspectives on the climate risk exposure of this sector. In line with this, it would also be interesting to analyze why the Climate Beta, and consequently $\Sigma MCRISK$ became negative in December 2022.

Given the large differences in $\Sigma CRISK$ and $\Sigma MCRISK$ in the observed countries, it could also be fruitful to analyze the dynamics of these variables in a single country in more detail.

Furthermore, considering alternative climate risk factors, such as a carbon tax, in the assessment of CRISK could provide a more comprehensive understanding. In addition, a more holistic assessment could be provided by conducting a bottom-up stress test approach to estimate financial institutions' exposure to transition risk and then comparing the results or by analyzing the loan and equity portfolios of individual financial institutions to find explanations for varying CRISK.

6. Conclusion

This research thesis has conducted an analysis of the climate-related transition risk exposure of 237 listed financial institutions operating in the Eurozone, applying a top-down market-based stress testing methodology as introduced by Jung et al. (2023). This represents a theoretical contribution by the novel application of this methodology on financial institutions in the Eurozone.

The results of this research show that in the context of a climate stress scenario, defined as a six-month decline in the returns by 50% of the climate risk proxy, represented by the Stranded Asset Portfolio, the analyzed financial institutions consistently exhibit a positive $\Sigma CRISK$, representing the aggregated capital shortfall under the climate risk scenario, over the observation period.

This positive $\Sigma CRISK,$ which represents the amount of capital injection the financial system would require in the climate stress scenario, implies that transition risk poses a systemic risk to the financial sector in the Eurozone.

In addition, the analyzed financial institutions exhibit a positive average $\Sigma MCRISK,$ which represents the increase of the expected capital shortfall in a stressed compared to a non-stressed scenario, isolating the portion of capital shortfall deriving from climate risk from the portion that is caused due to the undercapitalization of banks. The positive mean $\Sigma MCRISK$ highlights the potential of transition risks to amplify systemic financial vulnerabilities within the Eurozone.

Further, CRISK and MCRISK is concentrated within specific countries, industries and financial institutions.

These findings underscore the effect a transition risk stress scenario may have on financial stability and emphasize the need to strengthen the resilience and stability of the financial system in the face of climate uncertainties and for policymakers to aim to reduce climate policy risk by implementing expected, credible, and time-consistent climate policies.

7. Bibliography

Acharya, V. V., Berner, R., Engle, R., Jung, H., Stroebel, J., Zeng, X., & Zhao, Y. (2023). *Climate Stress Testing*. Federal Reserve Bank of New York Staff Reports, No. 1059, Federal Reserve Bank of New York. https://www.newyorkfed.org/medialibrary/media/research/staff_reports/sr1059.pdf [Last access: 28/08/2023]

Alessi, L., Balduzzi, P., & Savona, R. (2019). *Anatomy of a Sovereign Debt Crisis: CDS Spreads and Real-Time Macroeconomic Data.* JRC Working Papers in Economics and Finance, Publications Office of the European Union, Luxembourg, *ISBN 978-92-76-00120-1.* https://doi.org/10.2760/761074 [Last access: 31/07/2023]

Alessi, L., Ossola, E., & Panzica, R. (2021). "What greenium matters in the stock market? The role of greenhouse gas emissions and environmental disclosures". *Journal of Financial Stability*, 54(2021): 1-18. https://doi.org/10.1016/J.JFS.2021.100869 [Last access: 11/08/2023]

Allen, T., Dées, S., Caicedo, M., Chouard, V., Clerc, L., de Gaye, A., Devulder, A., Diot, S., Lisack, N., Pegoraro, F., Rabate, M., Svartzman, R., & Vernet, L. (2020). *Climate-Related Scenarios for Financial Stability Assessment: An Application to France*. Banque de France Working Paper, No.774, Banque de France. https://doi.org/10.2139/ssrn.3653131 [Last access: 29/08/2023]

Alogoskoufis, S., Dunz, N., Emambakhsh, T., Hennig, T., Kaijser, M., Kouratzoglou, C., Muñoz, M. A., Parisi, L., & Salleo, C. (2021). *ECB economy-wide climate stress test: Methodology and results.* Occasional Paper Series, No.281, European Central Bank. https://doi.org/10.2866/460490 [Last access: 13/08/2023]

Barnett, M. (2023). "A Run on Oil? Climate Policy and Stranded Assets Risk". *SSRN Electronic Journal*. https://doi.org/10.2139/ssrn.4346525 [Last access: 26/07/2023]

Basel Committee on Banking Supervision. (2021a). *Climate-related financial risks - measurement methodologies*. Bank for International Settlements. https://www.bis.org/bcbs/publ/d518.pdf [Last access: 06/03/2023]

Basel Committee on Banking Supervision. (2021b). *Climate-related risk drivers and their transmission channels.* Bank for International Settlements. https://www.bis.org/bcbs/publ/d517.pdf [Last access: 19/07/2023]

Battiston, S., Dafermos, Y., & Monasterolo, I. (2021). "Climate risks and financial stability". *Journal of Financial Stability,* 54: 1-6. https://doi.org/10.1016/j.jfs.2021.100867 [Last access: 16/08/2023]

Battiston, S., Mandel, A., Monasterolo, I., Schütze, F., & Visentin, G. (2017). "A climate stress-test of the financial system". *Nature Climate Change*, 7(4): 283–288. https://doi.org/10.1038/nclimate3255 [Last access: 16/03/2023]

Baudino, P., Goetschmann, R., Henry, J., Taniguchi, K., & Zhu, W. (2018). *Stress-testing banks – a comparative analysis,* FSI Insights on Policy Implementation, No.12, Bank for International Settlements. https://www.bis.org/fsi/publ/insights12.htm [Last access: 13/08/2023]

Bolton, P., & Kacperczyk, M. (2021). "Do investors care about carbon risk?". *Journal of Financial Economics,* 142(2): 517–549. https://doi.org/10.1016/J.JFINECO.2021.05.008 [Last access: 13/08/2023]

Breusch, T. S., & Pagan, A. R. (1980). "The Lagrange Multiplier Test and its Applications to Model Specification in Econometrics". *The Review of Economic Studies*, 47(1): 239-253. https://doi.org/10.2307/2297111 [Last access: 26/07/2023]

Brown, S. J., & Warner, J. B. (1985). "Using daily stock returns: The case of event studies". *Journal of Financial Economics*, 14(1): 3–31. https://doi.org/10.1016/0304-405X(85)90042-X [Last access: 03/08/2023]

Brownlees, C., & Engle, R. (2017). *SRISK: a conditional capital shortfall measure of systemic risk*. Working Paper Series, No.37, European Systemic Risk Board. https://doi.org/10.2849/814038 [Last access: 21/03/2023]

Burke, M., Hsiang, S. M., & Miguel, E. (2015). "Global non-linear effect of temperature on economic production". *Nature Journal*, 527(7577): 235–239. https://doi.org/10.1038/nature15725 [Last access: 06/03/2023]

Caldecott, B., Clark, A., Koskelo, K., Mulholland, E., & Hickey, C. (2021). "Stranded Assets: Environmental Drivers, Societal Challenges, and Supervisory Responses". *Annual Review of Environment and Resources*, 46: 417–447. https://doi.org/10.1146/annurev-environ-012220-101430 [Last access: 26/08/2023]

Cambridge Institute for Sustainability Leadership (CISL). (2019). *Physical risk framework: Understanding the impacts of climate change on real estate lending and investment portfolios.* University of Cambridge Institute for Sustainability Leadership. www.cisl.cam.ac.uk/climatewise [Last access: 10/08/2023]

Campiglio, E., Dafermos, Y., Monnin, P., Ryan-Collins, J., Schotten, G., & Tanaka, M. (2018). "Climate change challenges for central banks and financial regulators". *Nature Climate Change*, 8(6):462–468. https://doi.org/10.1038/s41558-018-0175-0 [Last access: 14/08/2023]

Casellina, S., Pandolfo, G., & Quagliariello, M. (2020). "Applying the Pre-Commitment Approach to bottom-up stress tests: A new old story". *Journal of Economics and Business*, 118. https://doi.org/https://doi.org/10.1016/j.jeconbus.2020.105931 [Last access: 14/08/2023]

Centre for Research on the Epidemiology of Disasters (CRED). (2023). "EM-DAT - The International Disaster Database". Université Catholique de Louvain. https://public.emdat.be [Last access: 25/07/2023]

Chan-Lau, J. A. (2013). *Market-Based Structural Top-Down Stress Tests of the Banking System*. IMF Working Paper, No.88, International Monetary Fund. https://www.imf.org/external/pubs/ft/wp/2013/wp1388.pdf [Last access: 14/08/2023]

D'Agostino, R. B., Belanger, A., & D'Agostino, R. B. Jr. (1990). "A Suggestion for Using Powerful and Informative Tests of Normality". *The American Statistician*, 44(4): 316–321. https://doi.org/10.2307/2684359 [Last access: 14/08/2023]

Daniëls, T., Duijm, P., Liedorp, F., & Mokas, D. (2017). *A top-down stress testing framework for the Dutch banking sector.* Occasional Studies, No.15(3), De Nederlandsche Bank. https://www.dnb.nl/en/publications/research-publications/occasional-study/nr-3-2017-a-top-down-stress-testing-framework-for-the-dutch-banking-sector/ [Last access: 14/08/2023]

Daumas, L. (2023). "Financial stability, stranded assets and the low-carbon transition-A critical review of the theoretical and applied literatures". *Journal of Economic Survey*, 1–116. https://doi.org/10.1111/joes.12551 [Last access: 18/04/2023]

Despres, M., Hiebert, P., Christophersen, C., Fahr, S., Mazzacurati, J., Budnik, K., & Dées, S. (2021). *Climate-related risk and financial stability - ECB/ESRB Project Team on climate risk monitoring*. European Central Bank. https://doi.org/10.2866/913118 [Last access: 17/07/2023]

Eceiza, J., Harreis, H., Härtl, D., & Viscardi, S. (2020, June 1). *Banking imperatives for managing climate risk*. McKinsey & Company. https://www.mckinsey.com/capabilities/risk-and-resilience/our-insights/banking-imperatives-for-managing-climate-risk [Last access: 19/07/2023]

Emambakhsh, T., Giuzio, M., Mingarelli, L., Salakhova, D., & Spaggiari, M. (2022). *Climate-related risks to financial stability*. Financial Stability Review, No.1, European Central Bank. https://www.ecb.europa.eu/pub/financial-stability/fsr/html/ecb.fsr202205~f207f46ea0.en.html [Last access: 14/08/2023]

Eren, E., Merten, F., & Verhoeven, N. (2022). *Pricing of climate risks in financial markets: a summary of the literature.* BIS Papers, No.130, Bank for International Settlements. https://www.bis.org/publ/bppdf/bispap130.htm [Last access: 13/08/2023]

European Banking Authority. (2023, July 28). *EBA publishes the results of its 2023 EU-wide stress test*. European Banking Authority. https://www.eba.europa.eu/eba-publishes-results-its-2023-eu-wide-stress-test [Last access: 18/08/2023]

European Central Bank. (2021, July 8). *ECB presents action plan to include climate change considerations in its monetary policy strategy.* European Central Bank. https://www.ecb.europa.eu/press/pr/date/2021/html/ecb.pr210708_1~f104919225.en.html?ssp=1&setlang=de-DE&safesearch=moderate [Last access: 01/08/2023]

European Central Bank. (2022a). *2022 Climate Risk Stress test*. European Central Bank. https://doi.org/10.2866/97350 [Last access: 13/08/2023]
European Central Bank. (2022b, July 4). *ECB climate agenda 2022*. European Central Bank. https://www.ecb.europa.eu/press/pr/date/2022/html/ecb.pr220704_annex~cb39c2dcbb.en.pdf [Last access: 13/08/2023]

European Central Bank. (2022c). *ECB report on good practices for climate stress testing*, European Central Bank. https://www.bankingsupervision.europa.eu/ecb/pub/pdf/ssm.202212_ECBreport_on_good_practices_for_CST~539227e0c1.en.pdf [Last access: 13/08/2023]

European Central Bank. (2023a). *Climate change and banking supervision*. European Central Bank. https://www.bankingsupervision.europa.eu/about/climate/html/index.en.html [Last access: 15/08/2023]

European Central Bank. (2023b). *Climate change and the ECB.* European Central Bank. https://www.ecb.europa.eu/ecb/climate/html/index.en.html [Last access: 15/08/2023]

European Central Bank. (2023c). *European System of Financial Supervision.* European Central Bank. https://www.bankingsupervision.europa.eu/about/esfs/html/index.en.html#:~:text=The%20European%20System%20of%20Financial,financial%20supervision%20throughout%20the%20EU [Last access: 15/08/2023]

European Central Bank. (2023d). *Single Supervisory Mechanism.* European Central Bank. https://www.bankingsupervision.europa.eu/about/thessm/html/index.en.html [Last access: 15/08/2023]

European Central Bank. (2023e). *Stress tests.* European Central Bank. https://www.bankingsupervision.europa.eu/banking/tasks/stresstests/html/index.en.html [Last access: 15/08/2023]

European Commission. (2021). *European Climate Law*. Climate Action. https://climate.ec.europa.eu/eu-action/european-green-deal/european-climate-law_en#:~:text=of%20the%20economy-,Formal%20adoption,force%20on%2029%20July%202021 [Last access: 01/08/2023]

European Council. (2023, March 2). *Financing the climate transition*. Council of the European Union. https://www.consilium.europa.eu/en/policies/climate-finance/ [Last access: 15/08/2023]

European Environment Agency. (2023, April 21). *Economic losses from climate-related extremes in Europe (8th EAP).* European Environment Agency. https://www.eea.europa.eu/ims/economic-losses-from-climate-related [Last access: 12/08/2023]

European Parliament. (2020, October 8). *EU climate law: MEPs want to increase 2030 emissions reduction target to 60%.* European Parliament News. https://www.europarl.europa.eu/news/en/press-room/20201002IPR88431/eu-climate-law-meps-want-to-increase-2030-emissions-reduction-target-to-60 [Last access: 12/08/2023]

European Parliament. (2022). *Interactive timeline: a guide to climate change negotiations*. European Parliament. https://www.europarl.europa.eu/infographic/climate-negotiations-timeline/index_en.html#event-2022-11-20 [Last access: 01/08/2023]

European Parliament and European Council. (2013, June 26). *Regulation (EU) No 575/2013 of the European Parliament and of the Council of 26 June 2013 on prudential requirements for credit institutions and amending Regulation (EU) No 648/2012 (Text with EEA relevance).* EUR-Lex: Access to European Union Law. https://eur-lex.europa.eu/legal-content/EN/TXT/?uri=CELEX%3A02013R0575-20230101 [Last access: 20/03/2023]

European Union. (2023). *Countries using the euro.* European Union. https://european-union.europa.eu/institutions-law-budget/euro/countries-using-euro_en [Last access: 27/04/2023]

Eurostat. (2022). *Losses from climate change: €145 billion in a decade*. Eurostat. https://ec.europa.eu/eurostat/en/web/products-eurostat-news/-/ddn-20221024-1 [Last access: 12/08/2023]

Eurostat. (2023). *Business Cycle Clock*. Eurostat. https://ec.europa.eu/eurostat/cache/bcc/bcc.html [Last access: 31/07/2023]

Faiella, I., Lavecchia, L., Michelangeli, V., & Mistretta, A. (2022). "A climate stress test on the financial vulnerability of Italian households and firms". *Journal of Policy Modeling*, 44(2): 396–417. https://doi.org/10.1016/j.jpolmod.2021.11.001 [Last access: 01/03/2023]

Farmer, J. D., Kleinnijenhuis, A. M., Schuermann, T., & Wetzer, T. (2022). *Handbook of Financial Stress Testing*. Cambridge: Cambridge University Press. https://doi.org/10.1017/9781108903011 [Last access: 13/08/2023]

Fofrich, R., Tong, D., Calvin, K., De Boer, H. S., Emmerling, J., Fricko, O., Fujimori, S., Luderer, G., Rogelj, J., & Davis, S. J. (2020). "Early retirement of power plants in climate mitigation scenarios". *Environmental Research Letters*, 15(9). https://doi.org/10.1088/1748-9326/AB96D3 [Last access: 13/08/2023]

Hausman, J. A. (1978). "Specification Tests in Econometrics". *Econometrica*, 46(6):1251–1271. https://doi.org/10.2307/1913827 [Last access: 18/07/2023]

Hiebert, P. (2021, July 13). *Climate change will unevenly impact the European financial system*. VoxEU – Centre for Economic Policy Research https://cepr.org/voxeu/columns/climate-change-will-unevenly-impact-european-financial-system [Last access: 15/08/2023]

Hobelsberger, K., Kok, C., & Mongelli, F. P. (2023). *A tale of three crises: synergies between ECB tasks*. Occasional Paper Series, No. 305, European Central Bank. https://doi.org/10.2866/622341 [Last access: 31/07/2023]

Huang, H. H., Kerstein, J., & Wang, C. (2018). "The impact of climate risk on firm performance and financing choices: An International Comparison". *Journal of International Business Studies*, 49(5):633–656. https://doi.org/10.2307/48725173 [Last access: 11/08/2023]

International Labour Office. (2019). *Working on a warmer planet: The impact of heat stress on labour productivity and decent work*. International Labour Organization. https://www.ilo.org/global/publications/books/WCMS_711919/lang--en/index.htm [Last access: 11/08/2023]

IPCC. (2000). *Summary for Policymakers. Emission Scenarios. A Special Report of IPCC Working Group III of the Intergovernmental Panel on Climate Change*. Cambridge University Press. Cambridge University Press, Cambridge, UK and New York, NY, USA. https://www.ipcc.ch/site/assets/uploads/2018/03/sres-en.pdf [Last access: 11/08/2023]

IPCC. (2022). *Climate Change 2022: Impacts, Adaptation and Vulnerability. Contribution of Working Group II to the Sixth Assessment Report of the Intergovernmental Panel on Climate Change* (H.-O. Pörtner, D. C. Roberts, M. Tignor, E. S. Poloczanska, K. Mintenbeck, A. Alegría, M. Craig, S. Langsdorf, S. Löschke, V. Möller, A. Okem, & B. Rama, Eds.). Cambridge University Press. Cambridge University Press, Cambridge, UK and New York, NY, USA, 3056 pp. https://doi.org/10.1017/9781009325844 [Last access: 11/08/2023]

IPCC. (2023a). *Summary for Policymakers. In: Climate Change 2023: Synthesis Report. A Report of the Intergovernmental Panel on Climate Change. Contribution of Working Groups I, II and III to the Sixth Assessment Report of the Intergovernmental Panel on Climate Change* [Core Writing Team, H. Lee & J. Romero, (eds.)]. IPCC, Geneva, Switzerland, 34pp. https://doi.org/10.59327/IPCC/AR6-9789291691647.001 [Last access: 12/08/2023]

Jung, H., Engle, R., & Berner, R. (2023). *CRISK: Measuring the Climate Risk Exposure of the Financial System*. Rev. March 2023. Previous title: "Climate Stress Testing", (2021, September 1). Federal Reserve Bank of New York Staff Reports, No. 977, Federal Reserve Bank of New York. http://dx.doi.org/10.2139/ssrn.3931516 [Last access: 15/08/2023]

Kahn, M., Mohaddes, K., Ng, R., Pesaran, M., Raissi, M., & Yang, J.-C. (2019). *Long-Term Macroeconomic Effects of Climate Change*. IMF Working Papers, Vol. 2019: Issue 215, International Monetary Fund. https://doi.org/10.5089/9781513514598.001 [Last access: 06/03/2023]

Kalkuhl, M., & Wenz, L. (2020). "The impact of climate conditions on economic production. Evidence from a global panel of regions". *Journal of Environmental Economics and Management*, 103(2020):1-20. https://doi.org/10.1016/j.jeem.2020.102360 [Last access: 06/03/2023]

Kruse, T., Mohnen, M., & Sato, M. (2020). *Are financial markets aligned with climate action? New evidence from the Paris Agreement*. Centre for Climate Change Economics and Policy Working Paper 364 // Grantham Research Institute on Climate Change and the Environment Working Paper 333, London: London School of Economics and Political Science. https://www.lse.ac.uk/granthaminstitute/wp-content/uploads/2020/02/working-paper-333-Kruse-et-al.pdf [Last access: 27/08/2023]

Litterman, B. (2023). *Selling Stranded Assets: Profit, Protection, and Prosperity*. Intentional Endowments Network. https://www.intentionalendowments.org/selling_stranded_assets_profit_protection_and_prosperity [Last access: 24/04/2023]

Mandel, A., Tiggeloven, T., Lincke, D., Koks, E., Ward, P., & Hinkel, J. (2021). "Risks on global financial stability induced by climate change: the case of flood risks". *Climatic Change*, 166(4):1-24. https://doi.org/10.1007/s10584-021-03092-2 [Last access: 26/04/2023]

Matikainen, S. (2022, July 27). *What are stranded assets?* Grantham Research Institute on Climate Change and the Environment. https://www.lse.ac.uk/granthaminstitute/explainers/what-are-stranded-assets/ [Last access: 11/08/2023]

MSCI Inc. (2023a). *MSCI EMU Index (USD)*. MSCI Inc. https://www.msci.com/documents/10199/7395c222-b136-4372-baa7-a4480d7d003c [Last access: 20/03/2023]

MSCI Inc. (2023b). *The Global Industry Classification Standard (GICS)*. MSCI Inc. https://www.msci.com/our-solutions/indexes/gics [Last access: 27/04/2023]

NGFS. (2020). *Guide to climate scenario analysis for central banks and supervisors*. Network for Greening the Financial System. https://www.ngfs.net/sites/default/files/medias/documents/ngfs_guide_scenario_analysis_final.pdf [Last access: 12/08/2023]

Partnership for Carbon Accounting Financials (PCAF). (2022). *The Global GHG Accounting & Reporting Standard Part A: Financed Emissions. Second Edition.* Partnership for Carbon Accounting Financials (PCAF). https://carbonaccountingfinancials.com/files/downloads/PCAF-Global-GHG-Standard.pdf [Last access: 11/08/2023]

Ranganathan, J., Corbier, L., Schmitz, S., Oren, K. (2004). *The Greenhouse Gas Protocol: A Corporate Accounting and Reporting Standard*. World Business Council for Sustainable Development; World Resources Institute, Geneva, Switzerland, Washington, DC. https://ghgprotocol.org/sites/default/files/standards/ghg-protocol-revised.pdf [Last access: 08/08/2023]

Reinders, H. J., Schoenmaker, D., & van Dijk, M. (2023a). “A finance approach to climate stress testing”. *Journal of International Money and Finance*, 131(2023): 1-19. https://doi.org/10.1016/j.jimonfin.2022.102797 [Last access: 15/03/2023]

Reinders, H. J., Schoenmaker, D., & van Dijk, M. (2023b). *Climate Risk Stress Testing: A Conceptual Review*. Working Paper, Erasmus Platform for Sustainable Value Creation. https://doi.org/10.2139/ssrn.4362342 [Last access: 14/08/2023]

Schober, D., Etzel, T., Falter, A., Frankovic, I., Gross, C., Kablau, A., Lauscher, P., Ohls, J., Strobel, L., & Wilke, H. (2021). *Sensitivity analysis of climate-related transition risks in the German financial sector*. Technical Paper, No.13/2021, Deutsche Bundesbank. https://www.bundesbank.de/resource/blob/846100/fb86cfe515ff7d1c10c8f9fe19b297cf/mL/2021-13-technical-paper-data.pdf [Last access: 02/08/2023]

Semieniuk, G., Holden, P. B., Mercure, J.-F., Salas, P., Pollitt, H., Jobson, K., Vercoulen, P., Chewpreecha, U., Edwards, N. R., & Viñuales, J. E. (2022). “Stranded fossil-fuel assets translate to major losses for investors in advanced economies”. *Nature Climate Change*, 12: 532-538. https://doi.org/10.1038/s41558-022-01356-y [Last access: 11/08/2023]

Shah, A. (2023). *ASREG: Stata module to estimate rolling window regressions, Fama-MacBeth and by(group) regressions*. Statistical Software Components, Boston College Department of Economics. https://ideas.repec.org/c/boc/bocode/s458339.html [Last access: 29/08/2023]

Simpson, N. P., Mach, K. J., Constable, A., Hess, J., Hogarth, R., Howden, M., Lawrence, J., Lempert, R. J., Muccione, V., Mackey, B., New, M. G., O'Neill, B., Otto, F., Pörtner, H. O., Reisinger, A., Roberts, D., Schmidt, D. N., Seneviratne, S., Strongin, S., van Aalst, M., Totin, E., Trisos, C. H. (2021). "A framework for complex climate change risk assessment". *One Earth, 4(4):489–501*. https://doi.org/10.1016/J.ONEEAR.2021.03.005 [Last access: 10/08/2023]

Statista. (2023a, August 31). *Russia-Ukraine war 2022 – statistics & facts*. Statista. https://www.statista.com/topics/9087/russia-ukraine-war-2022 [Last access: 02/09/2023]

Statista. (2023b, June 20). *Annual greenhouse gas emissions worldwide from 1990 to 2021*. Statista. https://www.statista.com/statistics/1285502/annual-global-greenhouse-gas-emissions/ [Last access: 27/08/2023]

Stroebel, J., & Wurgler, J. (2021). "What do you think about climate finance?". *Journal of Financial Economics*, 142(2):487–498. https://doi.org/10.1016/J.JFINECO.2021.08.004 [Last access: 13/08/2023]

TCFD. (2017). *Recommendations of the Task Force on Climate-related Financial Disclosures.* Task Force on Climate-related Financial Disclosures. https://assets.bbhub.io/company/sites/60/2020/10/FINAL-2017-TCFD-Report-11052018.pdf [Last access: 11/08/2023]

The World Bank. (2023). *World Bank National Accounts Data, GDP (Current US$) - Euro Area.* The World Bank. https://data.worldbank.org/indicator/NY.GDP.MKTP.CD?end=2022&locations=XC&start=2003 [Last access: 20/07/2023]

Thomson Reuters Refinitiv. (2023). *Screener*. Refinitiv Eikon. https://emea1.apps.cp.thomsonreuters.com/web/Apps/Homepage [Last access: 22/07/2023]

UNFCCC. (2023). *The Paris Agreement. What is the Paris Agreement?* United Nations Climate Change. https://unfccc.int/process-and-meetings/the-paris-agreement [Last access: 18/07/2023]

United Nations. (2021). *COP26: Together for our planet.* United Nations. https://www.un.org/en/climatechange/cop26 [Last access: 01/08/2023]

United Nations. (2023). *What is Climate Change?* United Nations Climate Action. https://www.un.org/en/climatechange/what-is-climate-change [Last access: 18/07/2023]

Van Riet, A. (2010). *Euro Area Fiscal Policies and the Crisis*. Occasional Paper Series, No. 109, European Central Bank. https://www.ecb.europa.eu/pub/pdf/scpops/ecbocp109.pdf [Last access: 31/07/2023]

Vermeulen, R., Schets, E., Lohuis, M., Kölbl, B., Jansen, D.-J., & Heeringa, W. (2018). *An energy transition risk stress test for the financial system of the Netherlands*. Occasional Studies, Vol.16-7, De Nederlandsche Bank. https://www.dnb.nl/en/publications/research-publications/occasional-study/nr-7-2018-an-energy-transition-risk-stress-test-for-the-financial-system-of-the-netherlands/ [Last access: 17/03/2023]

Walther, U. (2023). *EU Monitor Global financial markets: Climate Stress Tests*. Deutsche Bank. https://inside-research.db.com [Last access: 13/08/2023]

Welsby, D., Price, J., Pye, S., & Ekins, P. (2021). "Unextractable fossil fuels in a 1.5 °C world". *Nature Journal*, 597(2021): 230-240. https://doi.org/10.1038/s41586-021-03821-8 [Last access: 11/08/2023]

Woolridge, J. M. (2010). "Econometric Analysis of Cross Section and Panel Data". MIT Press Books, The MIT Press, Cambridge, Massachusetts. https://doi.org/10.1515/humr.2003.021 [Last access: 18/07/2023]

World Meteorological Organization (WMO). (2022). *State of the Climate in Europe 2021*. World Meteorological Organization (WMO). https://public.wmo.int/en/our-mandate/climate/wmo-statement-state-of-global-climate/Europe-2022 [Last access: 12/08/2023]

Xoual, W. (2013). *The Evolution of Stress Testing in Europe.* Moody's Analytics Risk Perspectives, Vol.1, Moody´s Analytics. https://www.moodysanalytics.com/-/media/article/2013/2013-01-09-risk-perspectives-v01-stress-testing-european-edition.pdf [Last access: 13/08/2023]

8. Appendix

8.1. Definition of Scope 1,2 and 3 GHG Emissions

The Greenhouse Gas Protocol introduced a corporate accounting and reporting standard that divides GHG emissions into three distinct scopes: Scope 1, scope 2, and scope 3 emissions (Ranganathan et al., 2004).

Scope 1 emissions refer to GHG emissions that originate from a company's internal production processes. *Scope 2* emissions, on the other hand, include GHG emissions attributed to electricity consumption, heating and cooling for the company's internal operations. *Scope 3* emissions include all indirect GHG emissions that occur in a company's value chain, which can contribute significantly to the overall GHG footprint.

For banks and financial institutions, scope 3 emissions reflect the combined scope 1 and 2 emissions of the companies in which they have invested or which they have financed. The calculation of these financed emissions requires an allocation of scope 1 and 2 GHG emissions from loans and investments to the scope 3 emissions of the reporting financial institution. The GHG Protocol Corporate Accounting and Reporting standard provides that this allocation is based on the proportion of the financial institution's lending or investment relative to the total value of the borrower's or investment recipient's equity and debt (Partnership for Carbon Accounting Financials (PCAF), 2022).

8.2. List of Financial Institutions

Table 16 presents all 237 financial institutions included in the data sample. For each company, the list includes its country of incorporation, its sub-industry name, and its rank by market capitalization as of December 31st 2022, which is in reference to the entire data sample. The companies in the list are arranged first by country, and within each country, they are further sorted based on their market capitalization as of December 31st 2022.

***Table 16**: List of Financial Institutions in Datasample*

Country of Incorporation	Company Name	Identifier (RIC)	GICS Sub-Industry Name	Market Cap #
Austria	Erste Group Bank AG	ERST.VI	Diversified Banks	14
	Raiffeisen Bank International AG	RBIV.VI	Diversified Banks	24
	BAWAG Group AG	BAWG.VI	Diversified Banks	28
	Oberbank AG	OBER.VI	Diversified Banks	31
	Bank fuer Tirol und Vorarlberg AG	TIRO.VI	Diversified Banks	52
	BKS Bank AG	KAER.VI	Diversified Banks	71
	Addiko Bank AG	ADKO.VI	Diversified Banks	103
	Wiener Privatbank SE	WPBI.VI	Asset Management & Custody Banks	156
	AB Effectenbeteiligungen AG	ABEV.VI	Asset Management & Custody Banks	223
Belgium	Kbc Groep NV	KBC.BR	Diversified Banks	11
	Gimv NV	GIMV.BR	Asset Management & Custody Banks	57
	Whitestone Group	ROCKW.BR	Asset Management & Custody Banks	160
	Candela Invest SA	CAND.BR	Asset Management & Custody Banks	185
	Beluga NV	BELU.BR	Asset Management & Custody Banks	189
	KBC Ancora BV	KBCA.BR	Diversified Banks	200
	Tinc Comm VA	TINCC.BR	Asset Management & Custody Banks	204
Croatia	Zagrebacka Banka dd	ZBB.ZA	Diversified Banks	38
	Hrvatska postanska banka dd	HPBZ.ZA	Diversified Banks	104
	Agram Banka dd	KBZA.ZA	Diversified Banks	140
	Istarska Kreditna Banka Umag dd	IKBA.ZA	Diversified Banks	144
	Podravska Banka dd	PDBA.ZA	Regional Banks	166
	Slatinska Banka dd	SNBA.ZA	Regional Banks	184
Cyprus	TCS Group Holding PLC	TCSq.L	Diversified Banks	43
	Hellenic Bank PCL	HBNK.CY	Diversified Banks	70
	Demetra Holdings Plc	DEM.CY	Asset Management & Custody Banks	124
	Phoenix Vega Mezz Plc	PVMEZZr.AT	Asset Management & Custody Banks	143
	LCP Holdings and Investments Public Ltd	LAIK.CY	Investment Banking & Brokerage	192
	Unigrowth Investments Public Ltd	UNIG.CY	Asset Management & Custody Banks	195
	CPI Holdings Public Ltd	CPIP.CY	Asset Management & Custody Banks	198
	Toriase Public Company Ltd	TORIA.CY	Asset Management & Custody Banks	201
	Aeonic Securities CIF PLC	AEON.CY	Investment Banking & Brokerage	231
	Aias Investment Public Ltd	AIAS.CY	Asset Management & Custody Banks	236
Estonia	LHV Group AS	LHV1T.TL	Diversified Banks	58
	Coop Pank AS	CPA1T.TL	Diversified Banks	102
	Investment Friends SE	IFRP.WA	Asset Management & Custody Banks	229
Finland	Nordea Bank Abp	NDAFI.HE	Diversified Banks	5
	eQ Oyj	EQV1V.HE	Asset Management & Custody Banks	60
	Aktia Bank Abp	AKTIA.HE	Regional Banks	68
	Oma Saastopankki Oyj	OMASP.HE	Regional Banks	73
	Alandsbanken Abp	ALBAV.HE	Diversified Banks	74
	CapMan Oyj	CAPMAN.HE	Asset Management & Custody Banks	83
	Evli Oyj	EVLI.HE	Asset Management & Custody Banks	87
	Taaleri Oyj	TAALA.HE	Asset Management & Custody Banks	96
	Titanium Oyj	TITAN.HE	Asset Management & Custody Banks	111

Country of Incorporation	Company Name	Identifier (RIC)	GICS Sub-Industry Name	Market Cap #
Finland	United Bankers Oyj	UNITED.HE	Diversified Capital Markets	113
	KH Group Oyj	KHG.HE	Asset Management & Custody Banks	131
	Alexandria Group Oyj	ALEX.HE	Asset Management & Custody Banks	134
	Inderes Oyj	INDERES.HE	Asset Management & Custody Banks	147
	Alisa Pankki Oyj	ALISA.HE	Diversified Banks	151
	Partnera Oyj	PARTNE1.HE	Asset Management & Custody Banks	155
	Springvest Oyj	SPRING.HE	Asset Management & Custody Banks	159
	Eagle Filters Group Oyj	EAGLE.HE	Asset Management & Custody Banks	180
France	BNP Paribas SA	BNPP.PA	Diversified Banks	1
	Credit Agricole SA	CAGR.PA	Diversified Banks	7
	Societe Generale SA	SOGN.PA	Diversified Banks	13
	Amundi SA	AMUN.PA	Asset Management & Custody Banks	17
	Tikehau Capital SCA	TKOO.PA	Asset Management & Custody Banks	27
	Antin Infrastructure Partners SAS	ANTIN.PA	Asset Management & Custody Banks	32
	Rothschild & Co SCA	ROTH.PA	Diversified Capital Markets	37
	Caiss Regio Credi Agric Mutuel Paris Idf	CAIF.PA	Regional Banks	47
	Caisse Reg Credit Agric Mut Nord France	CNDF.PA	Regional Banks	62
France	Caisse Regionale de Credit Agricole Mutuel Brie Picardie	CRBP2.PA	Regional Banks	63
	Altamir SCA	ALMP.PA	Asset Management & Custody Banks	64
	Caisse Regionale de Credit Agricole Mutuel du Languedoc	CRLA.PA	Regional Banks	65
	Caisse Reg Cred Agric Mut Atlantique Ven	CALCi.PA	Regional Banks	75
	Caisse Regionale De Credit Agricole Mutuel Sud Rhone Alpes	CRSU.PA	Regional Banks	76
	Credit Agricole Alpes Provence	CRAP.PA	Regional Banks	81
	Cr Credit Agricole Mutuel Loire Hte Loir	CRLO.PA	Regional Banks	82
	Caisse Regionale de Credit Agricole Mutuel de Normandie Seine SC	CCNP.PA	Regional Banks	85
	Chemin Fer Tramways Var Gard SA	TWVG.EUA	Asset Management & Custody Banks	88
	Viel et Compagnie SA	VEIL.PA	Investment Banking & Brokerage	90
	Caisse Reg Cred Agric Mut Tourain Poitou	CRTO.PA	Regional Banks	92
	IDI SCA	IDVP.PA	Asset Management & Custody Banks	94
	Caisse Regionale De Credit Agricole Mutuel Toulouse 31	CAT31.PA	Regional Banks	95
	Credit Agricole du Morbihan SC	CMO.PA	Regional Banks	98
	Caisse regionale de Credit Agricole Mutuel d’Ille-et-Vilaine	CIV.PA	Regional Banks	99

Country of Incorporation	Company Name	Identifier (RIC)	GICS Sub-Industry Name	Market Cap #
France	Caisse regionale de Credit Agricole Mutuel d'Ille-et-Vilaine	CIV.PA	Regional Banks	99
	Bourse Direct et Bourse Discount SA	BDRP.PA	Investment Banking & Brokerage	108
	Compagnie Lebon SA	ALBON.PA	Asset Management & Custody Banks	122
	Idsud SA	ALIDS.PA	Asset Management & Custody Banks	132
	Compagnie Des Tramways De Rouen SA	TRAM.EUA	Asset Management & Custody Banks	148
	Altur Investissement SCA	ALTUR.PA	Asset Management & Custody Banks	152
	Audacia SA	ALAUD.PA	Asset Management & Custody Banks	213
	Financiere Marjos SA	FINM.PA	Asset Management & Custody Banks	227
Germany	Deutsche Boerse AG	DB1Gn.DE	Financial Exchanges & Data	8
	Deutsche Bank AG	DBKGn.DE	Diversified Capital Markets	12
	Commerzbank AG	CBKG.DE	Diversified Banks	16
	DWS Group GmbH & Co KgaA	DWSG.DE	Asset Management & Custody Banks	22
	Tradegate AG Wertpapierhandelsbank	T2GG.F	Investment Banking & Brokerage	41
	Berliner Effektengesellschaft AG	BEFG.F	Investment Banking & Brokerage	59
	flatexDEGIRO AG	FTKn.DE	Investment Banking & Brokerage	69
	MLP SE	MLPG.DE	Asset Management & Custody Banks	72
	AURELIUS Equity Opportunities SE & Co KgaA	AR4G.H	Asset Management & Custody Banks	77
	Umweltbank AG	UBKG.DE	Diversified Banks	78
	Mutares SE & Co KgaA	MUXG.DE	Asset Management & Custody Banks	91
	BAVARIA Industries Group AG	B8AG.DE	Asset Management & Custody Banks	93
	OVB Holding AG	O4BG.DE	Asset Management & Custody Banks	97
	Euwax AG	EUXG.F	Investment Banking & Brokerage	100
	ProCredit Holding AG & Co KGaA	PCZ.DE	Diversified Banks	105
	JDC Group AG	JDC.DE	Investment Banking & Brokerage	106
	Baader Bank AG	BLMG.DE	Investment Banking & Brokerage	107
	Ernst Russ AG	HXCKk.DE	Asset Management & Custody Banks	112
	Laiqon AG	LQAG.DE	Asset Management & Custody Banks	114
	Sparta AG	SPTG.F	Asset Management & Custody Banks	117
	Blue Cap AG	B7EG.DE	Asset Management & Custody Banks	118
	Merkur Privatbank KGaA	MBKG.DE	Diversified Banks	119
	MPC Muenchmeyer Petersen Capital AG	MPCKk.DE	Asset Management & Custody Banks	121
	Netfonds AG	NF4.DE	Asset Management & Custody Banks	125
	Bitcoin Group SE	ADE.DE	Investment Banking & Brokerage	126
	Lang & Schwarz AG	LUS1n.DE	Investment Banking & Brokerage	127
	Shareholder Value Beteiligungen AG	SHVA.DE	Asset Management & Custody Banks	128
	SGT German Private Equity GmbH & Co KgaA	SGFn.DE	Asset Management & Custody Banks	129
	mwb Fairtrade Wertpapierhandelsbank AG	MWBG.DE	Investment Banking & Brokerage	136
	Finlab AG	A7AGn.DE	Asset Management & Custody Banks	139

Country of Incorporation	Company Name	Identifier (RIC)	GICS Sub-Industry Name	Market Cap #
Germany	Capsensixx AG	CPXG.DE	Asset Management & Custody Banks	141
	Effecten-Spiegel AG	EFSG.MU	Asset Management & Custody Banks	145
	Heliad Equity Partners GmbH & Co KGaA	HPBGn.DE	Asset Management & Custody Banks	146
	GBK Beteiligungen AG	GBQG.H	Asset Management & Custody Banks	149
	PEH Wertpapier AG	PEHG.F	Asset Management & Custody Banks	153
	Allerthal-Werke AG	ATWG.BE	Asset Management & Custody Banks	154
	Heidelberger Beteiligungsholding AG	IPOKk.F	Asset Management & Custody Banks	157
	Mountain Alliance AG	ECF1.DE	Asset Management & Custody Banks	158
	AdCapital AG	ADCG.F	Asset Management & Custody Banks	161
	Lehner Investments AG	LEH.F	Asset Management & Custody Banks	162
	Deutsche Effecten und Wechsel Beteiligungsgesellschaft AG	EFFG.DE	Asset Management & Custody Banks	164
	Coreo AG	COR2.DE	Asset Management & Custody Banks	165
	UCA AG	UCA1.F	Asset Management & Custody Banks	167
	NSI Asset AG	VMR1.F	Asset Management & Custody Banks	168
	Value-Holdings AG	VHOG.BE	Asset Management & Custody Banks	171
	Value-Holdings International AG	NW4G.BE	Asset Management & Custody Banks	172
	Murphy & Spitz Green Capital AG	MUSGn.D	Asset Management & Custody Banks	173
	Binect AG	MA10.DE	Asset Management & Custody Banks	175
	RM Rheiner Management AG	RMOG.D	Asset Management & Custody Banks	176
	DLB Anlageservice AG	DLBG.SG	Asset Management & Custody Banks	177
	KST Beteiligungs AG	KSWG.F	Asset Management & Custody Banks	181
	Horus AG	HRUG.MU	Asset Management & Custody Banks	182
	Venturio SE	3YO.D	Asset Management & Custody Banks	186
	Camerit AG	RTML.F	Asset Management & Custody Banks	187
	Stock3 AG	BOGn.MU	Financial Exchanges & Data	190
	Valora Effekten Handel AG	VEHG.F	Investment Banking & Brokerage	191
	Panamax AG	ICPG.F	Asset Management & Custody Banks	194
	Trade & Value AG	TAV.H	Asset Management & Custody Banks	197
	Deutsche Beteiligungs AG	DBANn.DE	Asset Management & Custody Banks	203
	Quirin Privatbank AG	QB7G.DE	Asset Management & Custody Banks	206
	Deutsche Balaton AG	BBHKk.F	Asset Management & Custody Banks	207
	Clere AG	CAG0n.H	Asset Management & Custody Banks	209
	sino AG	XTPG.DE	Investment Banking & Brokerage	211
	Varengold Bank AG	VG8G.DE	Investment Banking & Brokerage	214
	Elbstein AG	EBSG.H	Asset Management & Custody Banks	216
	Immovaria Real Estate AG	IR1.MU	Asset Management & Custody Banks	217
	Hoevelrat Holding AG	C9TG.H	Asset Management & Custody Banks	218
	Sci AG	SCIG.H	Asset Management & Custody Banks	220
	Tokentus Investment AG	14Dn.DE	Asset Management & Custody Banks	221
	ERWE Immobilien AG	ERWE.F	Asset Management & Custody Banks	222
	Q-Soft Verwaltungs AG	QS6A.SG	Asset Management & Custody Banks	224
	Instant Group AG	CCBG.MU	Asset Management & Custody Banks	225
	Konsortium AG	KUB1G.MU	Asset Management & Custody Banks	226
	PlanetHome Investment AG	ILK1.SG	Asset Management & Custody Banks	228
	DNI Beteiligungen AG	DNIG.BE	Asset Management & Custody Banks	230
	Auden AG	AD10k.MU	Asset Management & Custody Banks	233

Country of Incorporation	Company Name	Identifier (RIC)	GICS Sub-Industry Name	Market Cap #
Germany	Fritz Nols AG	FNGG.F	Investment Banking & Brokerage	234
	Red Rock Capital AG	BYBKk.BE	Asset Management & Custody Banks	235
	Schnigge Capital Markets SE	SHB3.D	Investment Banking & Brokerage	237
Greece	Eurobank Ergasias Services and Holdings SA	EURBr.AT	Diversified Banks	29
	National Bank of Greece SA	NBGr.AT	Diversified Banks	33
	Alpha Services and Holdings SA	ACBr.AT	Diversified Banks	44
	Piraeus Financial Holdings SA	BOPr.AT	Diversified Banks	48
	Hellenic Exchanges Athens Stock Exchange SA	EXCr.AT	Financial Exchanges & Data	109
	Attica Bank SA	BOAr.AT	Diversified Banks	120
	Alpha Trust Mutual Fund and Alternative Investment Fund Management SA	ATRSr.AT	Asset Management & Custody Banks	169
	CNL Capital EKES AIFM	CNLCAr.AT	Asset Management & Custody Banks	183
Ireland	Aib Group PLC	AIBG.I	Diversified Banks	18
	Bank of Ireland Group PLC	BIRG.I	Diversified Banks	19
	Permanent TSB Group Holdings PLC	PTSB.I	Diversified Banks	61
	Bank of Cyprus Holdings PLC	BOCH.CY	Diversified Banks	67
Italy	Intesa Sanpaolo SpA	ISP.MI	Diversified Banks	4
	UniCredit SpA	CRDI.MI	Diversified Banks	10
	FinecoBank Banca Fineco SpA	FBK.MI	Diversified Banks	20
	Banco BPM SpA	BAMI.MI	Diversified Banks	25
	Banca Generali SpA	BGN.MI	Asset Management & Custody Banks	30
	Azimut Holding SpA	AZMT.MI	Asset Management & Custody Banks	36
	Bper Banca SpA	EMII.MI	Diversified Banks	40
	Banca Monte dei Paschi di Siena SpA	BMPS.MI	Diversified Banks	42
	Credito Emiliano SpA	EMBI.MI	Diversified Banks	45
	Banca Popolare Di Sondrio SpA	BPSI.MI	Diversified Banks	49
	Anima Holding SpA	ANIM.MI	Asset Management & Custody Banks	55
	Tamburi Investment Partners SpA	TIP.MI	Asset Management & Custody Banks	56
	Banco di Desio e della Brianza SpA	DESI.MI	Diversified Banks	86
	Equita Group SpA	EQUI.MI	Investment Banking & Brokerage	110
	Banca Profilo SpA	PRO.MI	Investment Banking & Brokerage	115
	Banca Sistema SpA	BSTA.MI	Diversified Banks	116
	Intermonte Partners Sim SpA	INTM.MI	Investment Banking & Brokerage	130
	Directa SIM SpA	DS.MI	Investment Banking & Brokerage	135
	First Capital SpA	FICP.MI	Asset Management & Custody Banks	138
	Digital Magics SpA	DMG.MI	Asset Management & Custody Banks	150
	LVenture Group SpA	LVEN.MI	Asset Management & Custody Banks	163
	Confinvest FL SpA	CFVT.MI	Financial Exchanges & Data	170
	Copernico SIM SpA	COPE.MI	Asset Management & Custody Banks	174

Country of Incorporation	Company Name	Identifier (RIC)	GICS Sub-Industry Name	Market Cap #
Italy	Solutions Capital Management SIM SpA	SCM.MI	Asset Management & Custody Banks	178
	Gequity SpA	GEQ.MI	Asset Management & Custody Banks	179
	Ambromobiliare SpA	AMBA.MI	Asset Management & Custody Banks	188
	Mediobanca Banca di Credito Finanziario SpA	MDBI.MI	Diversified Banks	199
	H-Farm SpA	HFARM.MI	Asset Management & Custody Banks	212
Lithuania	Siauliu Bankas AB	SAB1L.VL	Diversified Banks	84
Luxembourg	Reinet Investments SCA	REIT.LU	Asset Management & Custody Banks	34
	Brederode SA	BREL.LU	Asset Management & Custody Banks	35
	Luxempart SA	LUXP.LU	Asset Management & Custody Banks	51
	BBGI Global Infrastructure SA	BBGIB.L	Asset Management & Custody Banks	53
Malta	Bank of Valletta PLC	BOV.MT	Diversified Banks	79
	Brait PLC	BATJ.J	Asset Management & Custody Banks	101
	FIMBank plc	FIM.MT	Diversified Banks	133
	HSBC Bank Malta PLC	HSB.MT	Diversified Banks	205
	Cryptology Asset Group PLC	SRAG.F	Asset Management & Custody Banks	208
Malta	Lombard Bank Malta PLC	LOM.MT	Regional Banks	210
Netherlands	ING Groep NV	INGA.AS	Diversified Banks	3
	ABN Amro Bank NV	ABNd.AS	Diversified Banks	15
	Euronext NV	ENX.PA	Financial Exchanges & Data	21
	Van Lanschot Kempen NV	VLAN.AS	Asset Management & Custody Banks	66
	Value8 NV	VALU8.AS	Asset Management & Custody Banks	137
	Navstone SE	NUQA.SG	Asset Management & Custody Banks	219
Portugal	Banco Comercial Portugues SA	BCP.LS	Diversified Banks	46
	Flexdeal SIMFE SA	FLEXD.LS	Asset Management & Custody Banks	215
Slovakia	Tatra Banka as	1TAT01DE.BV	Diversified Banks	50
	Vseobecna Uverova Banka as	1VUB02AE.BV	Diversified Banks	202
Slovenia	Nova Ljubljanska Banka dd Ljubljana	NLBR.LJ	Diversified Banks	54
	KD dd	SKDR.LJ	Asset Management & Custody Banks	142
	KS Nalozbe dd	KSFR.LJ	Asset Management & Custody Banks	193
	Vipa Holding dd	VHDR.LJ	Investment Banking & Brokerage	232
Spain	Banco Santander SA	SAN.MC	Diversified Banks	2
	Banco Bilbao Vizcaya Argentaria SA	BBVA.MC	Diversified Banks	6
	Caixabank SA	CABK.MC	Diversified Banks	9
	Bankinter SA	BKT.MC	Diversified Banks	23
	Banco de Sabadell SA	SABE.MC	Diversified Banks	26
	Unicaja Banco SA	UNI.MC	Diversified Banks	39
	Alantra Partners SA	ALNTA.MC	Investment Banking & Brokerage	80
	Renta 4 Banco SA	RTA4.MC	Investment Banking & Brokerage	89
	Axon Partners Group SA	APG.MC	Asset Management & Custody Banks	123
	Union Catalana de Valores SA	UCAV.SCT	Investment Banking & Brokerage	196

Source: Thomson Reuters Refinitiv (2023)

8.3. Observed Companies by Country

Table 17 shows an overview of the observed countries and the distribution of observed companies by number and average aggregate market capitalization. The dataset does not contain any financial institution with its country of incorporation in Latvia. The absence of such companies is attributable to the circumstance that after filtering by GICS industry name and retrieving relevant financial companies from Refinitiv Eikon, only one company in Latvia was identified. However, this company was missing a variable that was essential for conducting further analysis. Therefore, the company was excluded from the dataset to ensure the accuracy of the subsequent analyses.

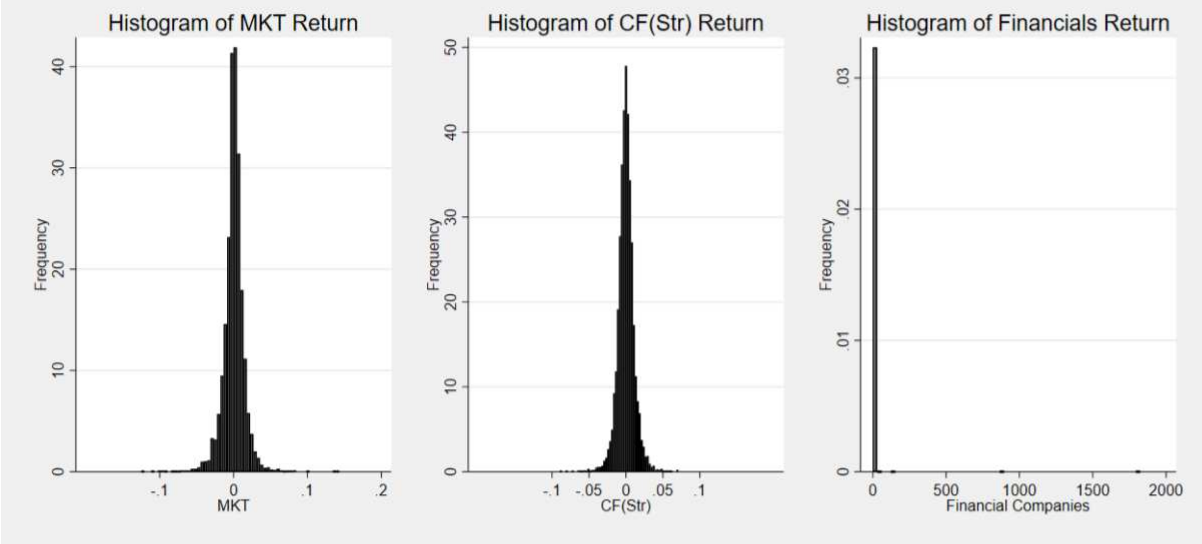
Table 17: *Observed Companies by Country*

Country	# Companies	%	Market Capitalization (billion EUR)	%
Austria	9	*3,8*	22,08	*3,6%*
Belgium	7	*3,0*	24,79	*4,0%*
Croatia	6	*2,5*	2,63	*0,4%*
Cyprus	10	*4,2*	1,79	*0,3%*
Estonia	3	*1,3*	0,28	*0,0%*
Finland	17	*7,2*	32,71	*5,3%*
France	31	*13,1*	131,36	*21,2%*
Germany	79	*33,3*	64,39	*10,4%*
Greece	8	*3,4*	17,87	*2,9%*
Ireland	4	*1,7*	26,46	*4,3%*
Italy	28	*11,8*	99,19	*16,0%*
Lithuania	1	*0,4*	0,16	*0,0%*
Luxembourg	4	*1,7*	4,33	*0,7%*
Malta	6	*2,5*	2,83	*0,5%*
Netherlands	6	*2,5*	50,62	*8,2%*
Portugal	2	*0,8*	4,15	*0,7%*
Slovakia	2	*0,8*	1,41	*0,2%*
Slovenia	4	*1,7*	0,39	*0,1%*
Spain	10	*4,2*	133,36	*21,5%*

Source: Thomson Reuters Refinitiv (2023)

8.4. Supplementary Summary Statistics

Figure 19: *Histograms of MKT, CF(Str) and Financial Institutions Daily Return*



These graphs show the distribution of daily returns of the Market Portfolio MKT, the Stranded Asset Portfolio, and the financial institutions. As the histogram of financial return shows, there are several significant outliers, which is why the financials daily return data was winsorized for the subsequent regression analysis.

Source: Own illustration

8.4.1. Independent Variables

Table 18: *Skewness and Kurtosis Test for Normality for MKT_t* and *$CF_{Str,t}$ Daily Return*

				Joint Test	
Variable	**Obs**	**Pr(skewness)**	**Pr(kurtosis)**	**Adj chi2(2)**	**Prob>chi2**
$r_{MKT,t}$	5,218	0,0000	0,0000	750,95	0,0000
$r_{CF_{Str,t}}$	5,218	0,0009	0,0000	466,00	

Source: Own calculation

Table 19: *MKT_t and CF_t Daily Return Pairwise Correlation*

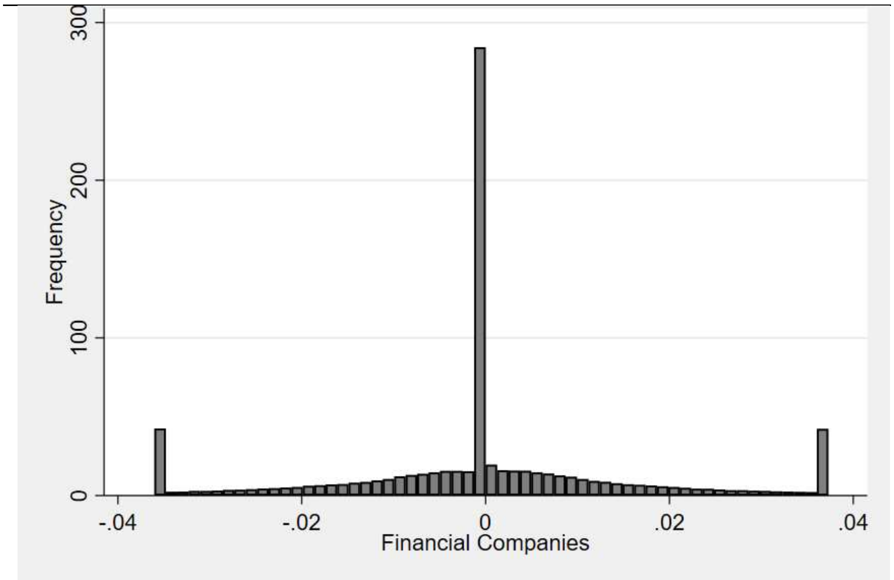
Variables	**(1)**	**(2)**
(1) $r_{MKT,t}$	1,000	
(2) $r_{CF_{Str},t}$	-0,547*	1,000

*Significance levels: *** p<0.01, ** p<0.05, * p<0.1*

Source: Own calculation

8.4.2. Dependent Variable

***Figure 20:** Histogram of Financials Return, winsorized*



The histogram shows the distribution of daily returns of the observed financial companies over the observation period, winsorized at the 5th and 95th percentile.

Source: Own illustration

8.5. Statistical Tests

***Table 20:** Hausman (1978) Specification Test*

Variable	Coefficients		Difference	Std. Err.
	(b) fixed	*(B) random*	*(b-B)*	*Sqrt(diag(V_b-V_B))*
$r_{MKT,t}$	0,21687	0,21687	3,48e-06	164,83
$r_{CF_{Str},t}$	0,10285	0,10283	0,0000188	61,64

b = consistent under H0 and H1; obtained from xtreg
B = Inconsistent under H1, efficient under H0; obtained from xtreg

Test of H0: Difference in coefficients not systematic
Chi-square Test Value = 4,344
Prob > Chi-square = 0,1139

Source: Own calculation

***Table 21:** Breusch Pagan (1980) Lagrange Multiplier Test*

Variable	Var	SD = Sqrt(Var)
$r_{CF_{Str},t}$_win5	0,0002635	0,0162322
e	0,0002557	0,0159919
u	1,91e-07	0,000437
Test: Var(u) = 0	Chibar-squared(01) = 864,89 Prob > Chibar2 = 0,0000	

Source: Own calculation

Table 22: *Woolridge (2002) Test for Autocorrelation in Panel Data*

H0: No first-order autocorrelation	F(1,236) = 119,720 Prob > F = 0,0000

Source: Own calculation

8.6. Comparison of Fixed Effects and Random Effects Fixed Beta Regression

Table 23: *Fixed Effects Regression Results*

Variable	**Coef.**	**St.Err.**	**t-value**	**p-value**	**[95% Conf**	**Interval]**	**Sig**
$r_{MKT,t}$	0,217	0,001	164,83	0	0,214	0,219	***
$r_{CF_{Str},t}$	0,103	0,002	61,65	0	0,1	0,106	***
Constant	0	0	-0,40	0,687	0	0	
Mean dependent var		0,000	SD dependent var			0,016	
			Number of obs			949222	
			Number of groups			237	
R-squared		Within = 0,0288	Obs per group:			Min= 111	
		Between = 0,0019				Avg= 4005,2	
		Overall = 0,0288				Max= 5218	
F-test		14061,984	Prob > F			0,000	
Akaike crit. (AIC)		-5157796,066	Bayesian crit. (BIC)			-5157760,776	

*Significance levels: *** p<0,01, ** p<0,05, * p<0,1*

Source: Own calculation

Table 24: *Random Effects Regression Results*

Variable	Coef.	St.Err.	t-value	p-value	[95% Conf	Interval]	Sig
$r_{MKT,t}$	0,217	0,001	164,83	0	0,214	0,219	***
$r_{CF_{Str},t}$	0,103	0,002	61,64	0	0,1	0,106	***
Constant	0	0	-0,26	0,792	0	0	
Mean dependent var		0,000	SD dependent var			0,016	
			Number of obs			949222	
			Number of groups			237	
R-squared		Within = 0,0288	Obs per group			Min= 111	
		Between = 0,0019				Avg= 4005,2	
		Overall = 0,0288				Max= 5218	
Wald Chi-square		28124,329	Prob > chi2			0,000	

*Significance levels: *** p<0,01, ** p<0,05, * p<0,1*

Source: Own calculation

8.7.Summary Statistics Rolling Window Regression

Table 25: *Summary Statistics Average Rolling Window Betas*

Summary Statistics	Average Climate Beta	Average Market Beta
Count	4957	4957
Mean	0,1179	0,2501
Standard Error	0,0009	0,0007
Median	0,1049	0,2517
Standard Deviation	0,0668	0,0471
Sample Variance	0,0045	0,0022
Kurtosis	0,3940	-0,4550
Skewness	0,8752	-0,2100
Range	0,3229	0,2117
Minimum	-0,0038	0,1391
Maximum	0,3191	0,3508
Confidence Level(95.0%)	0,0019	0,0013
Correlation		
Average Climate Beta	1	
Average Market Beta	0,272973889	1

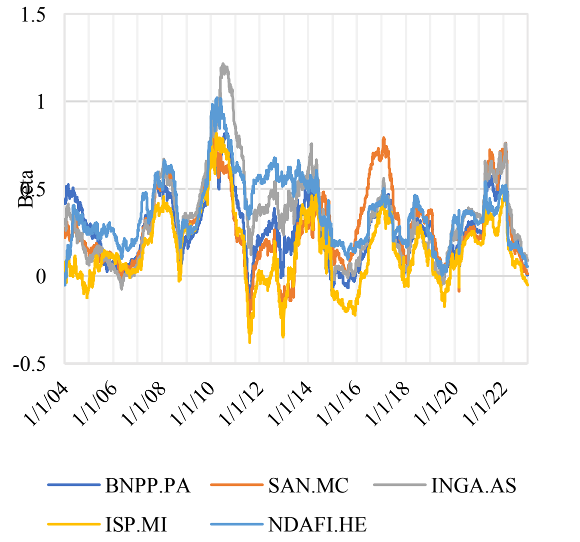
Source: Own calculation

8.8.Climate Betas Individual Rolling Window Regression

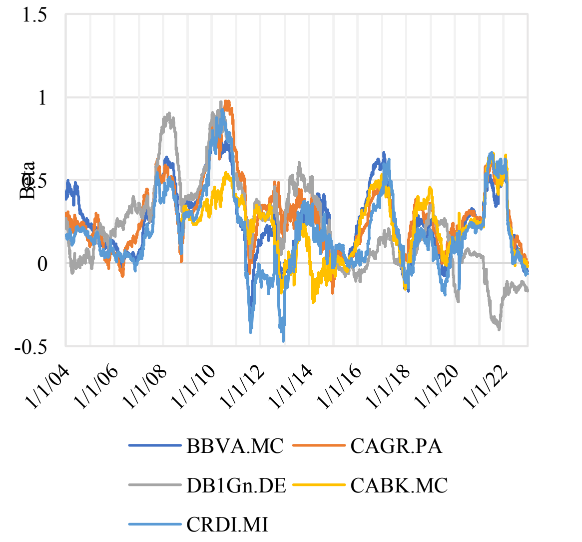
Figure 21 shows the individual rolling betas of the top 20 companies by market capitalization as of December 31st 2022.

Figure 21: *Rolling Betas of Top 20 Companies by Market Capitalization*

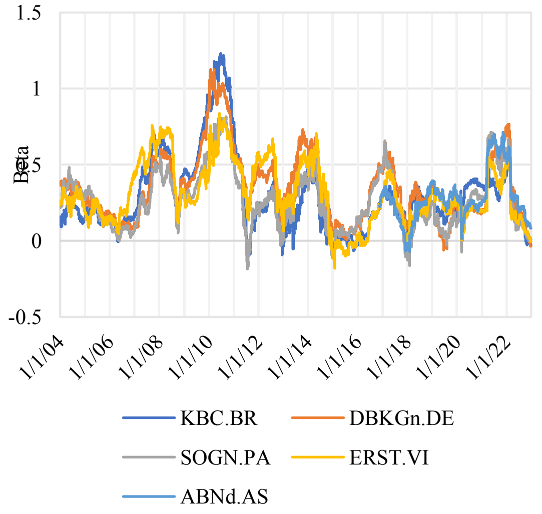
(1) Top 1-5 Companies



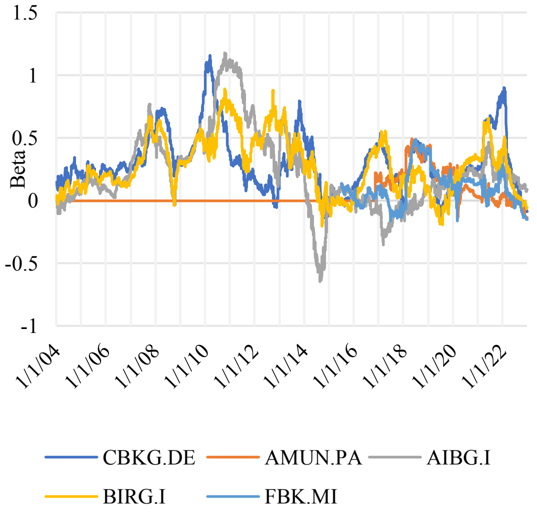
(2) Top 6-10 Companies



(3) Top 11-15 Companies



(4) Top 16-20 Companies



Source: Own illustration

8.9. Time-series evaluation of CRISK and MCRISK

Table 26: *Correlation of CRISK and MCRISK with Recession and Crisis Periods*

Correlation	CRISK	*p-value*	MCRISK	*p-value*
Recession Periods	0,2098	*0,0000*	0,1262	*0,0000*
Financial Crisis	0,0404	*0,0045*	0,3199	*0,0000*
Subprime Debt Crisis	0,3606	*0,0000*	0,2286	*0,0000*
Covid-19 Crisis	0,4986	*0,0000*	-0,0258	*0,0691*

Source: Own calculation

8.9.1. CRISK and MCRISK during Recession

Table 27: *CRISK and Marginal CRISK in Recession*

Average		CRISK	MCRISK
Entire Period		594,89	40,43
Recession		710,69	48,72
No Recession		573,11	38,87
	Delta	24,01%	25,34%
Until 06/2009		352,20	42,53
Post 06/2009		693,27	39,57
	Delta	96,84%	-6,95%

Source: Own calculation

Figure 22: *CRISK in Recession Periods*

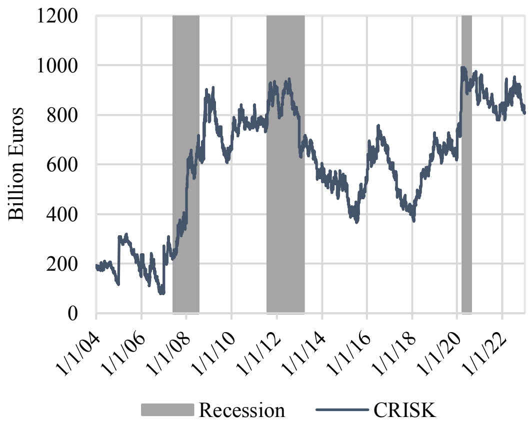
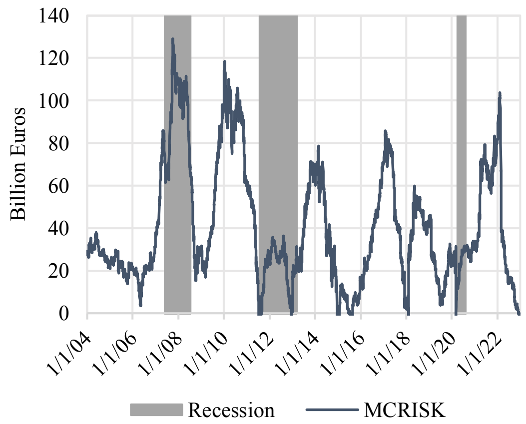


Figure 23: *MCRISK in recession periods*



The areas highlighted in grey indicate the presence of a recession.
Source: Own illustration

8.9.2. CRISK and MCRISK during Financial Crises

CRISK and MCRISK during Global Financial Crisis

Focusing on the global financial crisis, $\Sigma CRISK$ in the first shock period (07/2007-09/2007) increased significantly by 28,3% compared to the pre-crisis month. Overall, CRISK increased by 158,7% during the crisis. A plausible reason for this change in $\Sigma CRISK$ could be the decrease in the total market value of equity, which decreased by 5,6% during the first shock and by 35,1% during the entire crisis. Similarly, $\Sigma MCRISK$ increased by 26,5% during the first shock, followed by a slight decrease of 0,7% during the entire crisis. Additionally, the Climate Beta showed a significant increase of 23,7% during the first shock and an overall increase of 58,3% during the crisis.[13]

[13] In addition, a correlation analysis in Section 8.9 shows that the presence of a financial crisis has a significant positive correlation with CRISK and MCRISK.

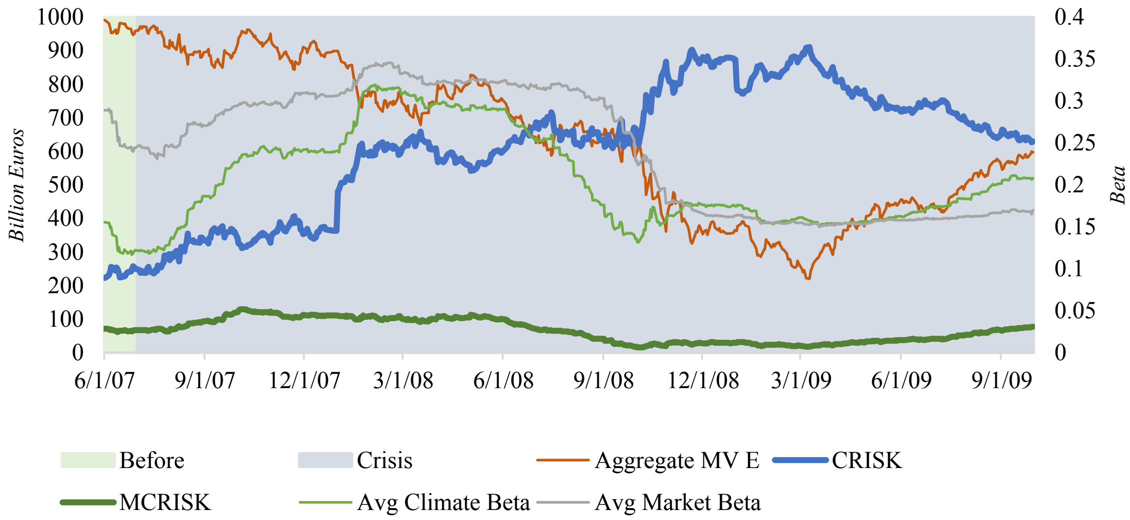
***Table 28:** Change of Variables During Global Financial Crisis*

	Pre Crisis	First Shock	*Delta*	Crisis	*Delta*
CRISK	240,10	308,15	*28,3%*	621,24	*158,7%*
MCRISK	65,74	83,15	*26,5%*	65,26	*-0,7%*
MV	965,59	911,12	*-5,6%*	626,39	*-35,1%*
Liabilities	13341,43	13351,74	*0,1%*	14131,52	*5,9%*
$\beta^{Climate}$	0,13	0,16	*23,7%*	0,21	*58,3%*
β^{Market}	0,26	0,26	*0,6%*	0,24	*-7,1%*

CRISK, MCRISK, MV and Liabilities are displayed in Billion Euros

Source: Own calculation

***Figure 24:** Change of Variables during Global Financial Crisis*



***Before:** Indicates 1-month pre-shock period*
***Left y-axis:** MV E, CRISK, MCRISK*
***Right y-axis:** Average Climate Beta, Average Market Beta*

Source: Own illustration

CRISK and MCRISK during Sovereign Debt Crisis

An analysis of $\Sigma CRISK$ and $\Sigma MCRISK$ during the European sovereign debt crisis shows that compared to the previously studied global financial crisis, the impact on $\Sigma CRISK$ and $\Sigma MCRISK$ is significantly lower.

$\Sigma CRISK$ increased by 23,7% during the European sovereign debt crisis compared to the month before the crisis, which is significantly less than the 158% increase observed during the global financial crisis. In contrast, the $\Sigma MCRISK$ declined by 21,8% during the European sovereign debt crisis.

To understand the reasons for the contrasting trend of $\Sigma CRISK$ and $\Sigma MCRISK$, the possible influencing factors are examined. The observed increase in $\Sigma CRISK$ during the European sovereign debt crisis can be partially attributed to a 16,1% decline in the total market value of equity. This decline in the market value of equity may explain the increase in $\Sigma CRISK$, as it indicates higher financial risk for firms during this crisis. The fact that the $\Sigma MCRISK$ fell by 21,8% during the European sovereign debt crisis, in contrast to the $\Sigma CRISK$, can be partially explained by the decline in the Climate Beta, which fell by 7,7% during the European sovereign debt crisis.

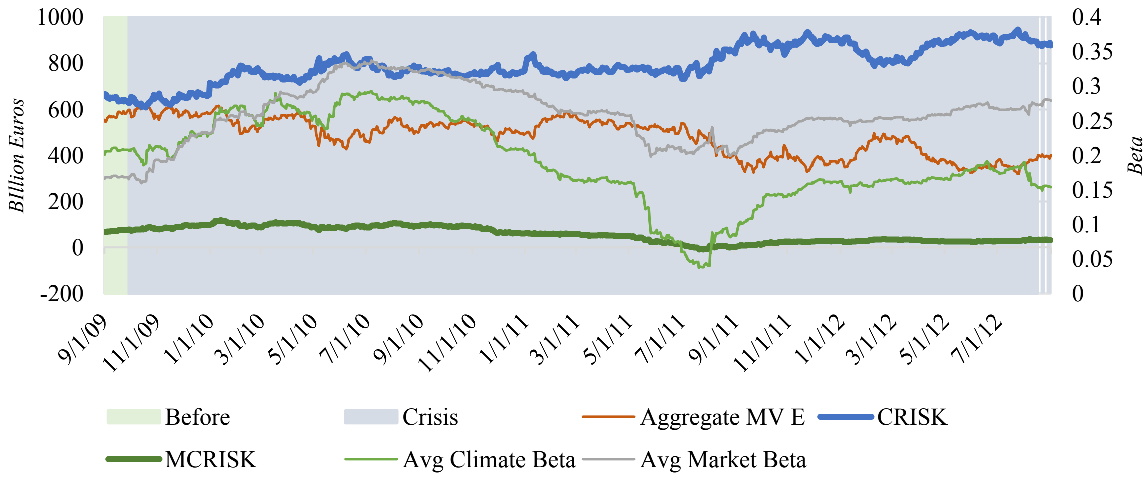
Table 29: *Change of Variables during Sovereign Debt Crisis*

	Pre Crisis	First Shock	*Delta*	Crisis	*Delta*
CRISK	644,50	645,04	*0,1%*	797,05	*23,7%*
MCRISK	71,30	86,70	*21,6%*	55,73	*-21,8%*
MV E	573,12	587,55	*2,5%*	480,70	*-16,1%*
Liabilities	13782,83	13775,65	*-0,1%*	14943,06	*8,4%*
$\beta^{Climate}$	0,21	0,21	*2,9%*	0,19	*-7,7%*
β^{Market}	0,17	0,20	*18,6%*	0,26	*55,5%*

CRISK, MCRISK, MV E and Liabilities are displayed in Billion Euros

Source: Own calculation

Figure 25: *Change of Variables during Sovereign Debt Crisis*



Before: *Indicates 1-month pre-shock period*
Left y-axis: *MV E, CRISK, MCRISK*
Right y-axis: *Average Climate Beta, Average Market Beta*

Source: Own illustration

CRISK and MCRISK during COVID-19 Pandemic

At the onset of the COVID-19 pandemic, there was an abrupt decline in the total market capitalization of the observed financial institutions, which plummeted by 27,3% during the first shock between February and April 2020 compared to January 2020. However, throughout the crisis period, market capitalization recovered significantly, declining by only 7,3% in total compared to pre-crisis levels. Coinciding with the decline in market capitalization, the $\Sigma CRISK$ recorded a remarkable 21,2% increase during the first shock of the pandemic. Contrarily, the behavior of $\Sigma MCRISK$ was opposite, as it decreased significantly by 18.3% during the same period. This opposite behavior cannot be explained by lower beta alone, as Climate Beta increased significantly by 63,8%.

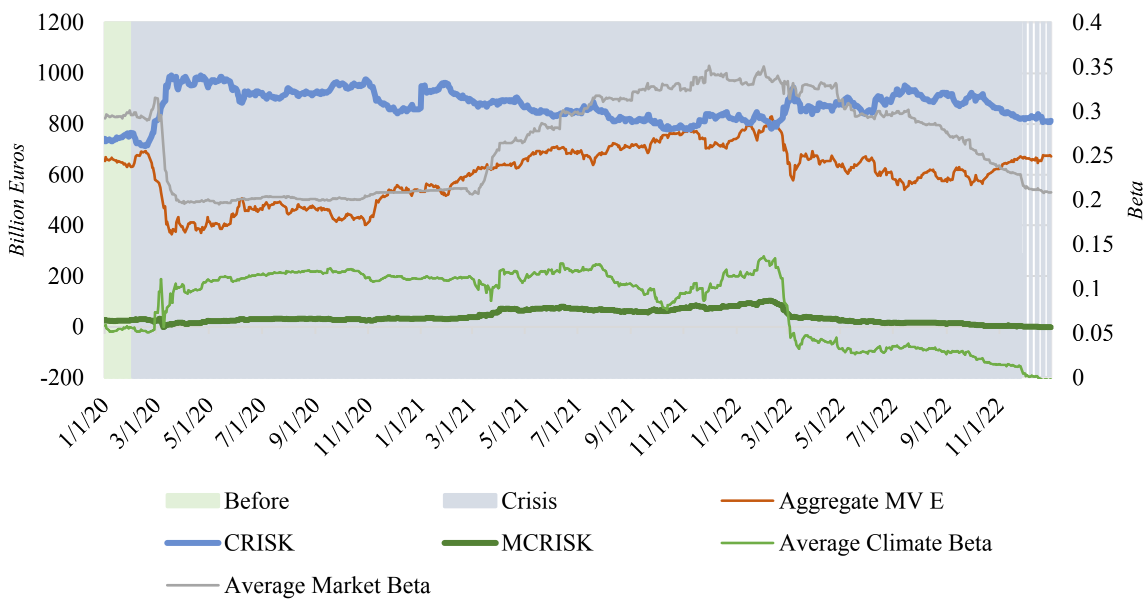
To understand the reasons for this counterintuitive trend between $\Sigma CRISK$ and $\Sigma MCRISK$, further research would be essential. However, over the entire COVID-19 crisis period, $\Sigma MCRISK$ experienced a substantial increase of 62,5% relative to pre-crisis levels, which is consistent with the simultaneous 55,8% increase of the Climate Beta. A plausible explanation for the continued rise in Climate Beta and $\Sigma MCRISK$ could be due to the increasing frequency of climate disasters and subsequent climate policy decisions by policymakers. These developments impose greater transition risks on companies, which could contribute to the observed increase in $\Sigma MCRISK$ and Climate Beta.

Table 30: *Change of Variables during COVID-19 Pandemic*

	Pre Crisis	**First Shock**	***Delta***	**Crisis**	***Delta***
CRISK	744,42	902,58	*21,2%*	875,18	*17,6%*
MCRISK	23,82	19,46	*-18,3%*	38,70	*62,5%*
MV E	650,28	472,79	*-27,3%*	602,59	*-7,3%*
Liabilities	16487,23	16478,49	*-0,1%*	17337,97	*5,2%*
$\beta^{Climate}$	0,05	0,09	*63,8%*	0,08	*55,8%*
β^{Market}	0,29	0,23	*-21,9%*	0,26	*-10,6%*

Source: Own calculation

__Figure 26:__ Change of Variables during COVID-19 Pandemic



***Before:** Indicates 1-month pre-shock period*
***Left y-axis:** MV E, CRISK, MCRISK*
***Right y-axis:** Average Climate Beta, Average Market Beta*

Source: Own illustration

8.10. Cross-Sectional evaluation of CRISK

8.10.1. CRISK and MCRISK by Company

__Table 31:__ Cumulative Average CRISK

Company	***Average CRISK***	***Share of total CRISK***		***Average CRISK / Average MV***
		%	*Cumulative %*	
BNPP.PA	98,88	16,60%	16,60%	165,80%
CAGR.PA	97,17	16,30%	33,00%	320,59%
DBKGn.DE	93,91	15,80%	48,80%	307,46%
SOGN.PA	65,74	11,10%	59,80%	214,27%
INGA.AS	44,98	7,60%	67,40%	107,75%
CRDI.MI	35,03	5,90%	73,30%	106,56%
SAN.MC	34,31	5,80%	79,10%	51,60%
CBKG.DE	33,23	5,60%	84,70%	312,09%
ISP.MI	18,62	3,10%	87,80%	53,14%
ABNd.AS	16,29	2,70%	90,50%	104,11%

This table displays the average CRISK in billion euros of the ten companies with the highest average CRISK value of the data sample.

Source: Own calculation

Table 32: *Cumulative Average MCRISK*

Company	***Average MCRISK***	***Share of total MCRISK*** *%*	*Cumulative %*	***Average CRISK / Average MV***
SAN.MC	5,07	12,50%	11,80%	7,62%
BNPP.PA	4,26	10,50%	21,70%	7,15%
INGA.AS	3,2	7,90%	29,20%	7,67%
NDAFI.HE	3,02	7,50%	36,20%	9,62%
DBKGn.DE	2,77	6,80%	42,70%	9,06%
BBVA.MC	2,73	6,80%	49,00%	6,59%
CAGR.PA	2,22	5,50%	54,20%	7,32%
SOGN.PA	2,12	5,30%	59,20%	6,93%
CRDI.MI	1,75	4,30%	63,20%	5,32%
ISP.MI	1,5	3,70%	66,70%	4,31%

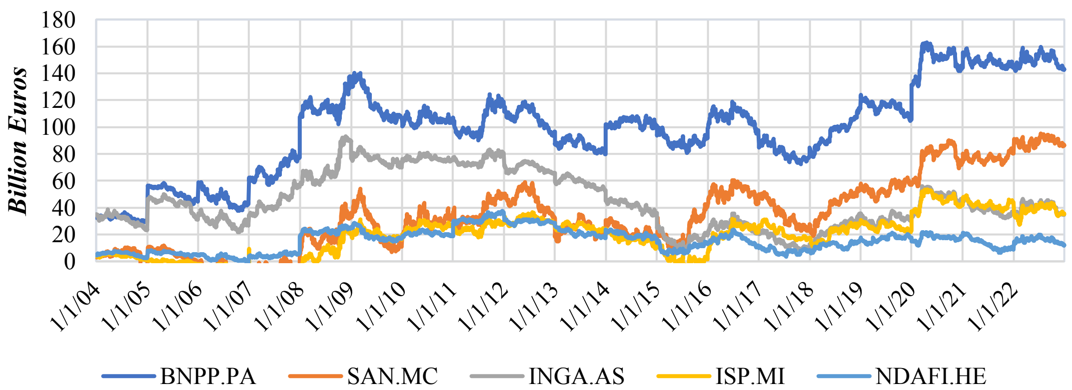
This table displays the average MCRISK in billion euros of the ten companies with the highest average MCRISK value of the data sample.
Source: Own calculation

Table 33: *CRISK Summary Statistics of Largest Companies by Market Capitalization*

	Mean	**Median**	**Std. Dev.**	**Min.**	**Max.**	**31.12.22**
BNPP.PA	98,88	103,15	32,87	29,02	162,92	143,41
SAN.MC	34,31	30,93	27,26	-18,79	95,23	86,47
INGA.AS	44,98	41,29	20,50	7,10	93,23	35,28
ISP.MI	18,62	22,21	16,19	-22,70	53,60	35,62
NDAFI.HE	15,43	16,29	8,32	-1,05	37,48	12,11
Other	382,18	414,52	156,47	35,91	628,26	498,24
Overall	**594,39**	**640,46**	**239,68**	**78,65**	**990,88**	**811,13**

This table displays CRISK of 5 largest companies by market capitalization as of 31/12/2022 in billion euros.
Source: Own calculation

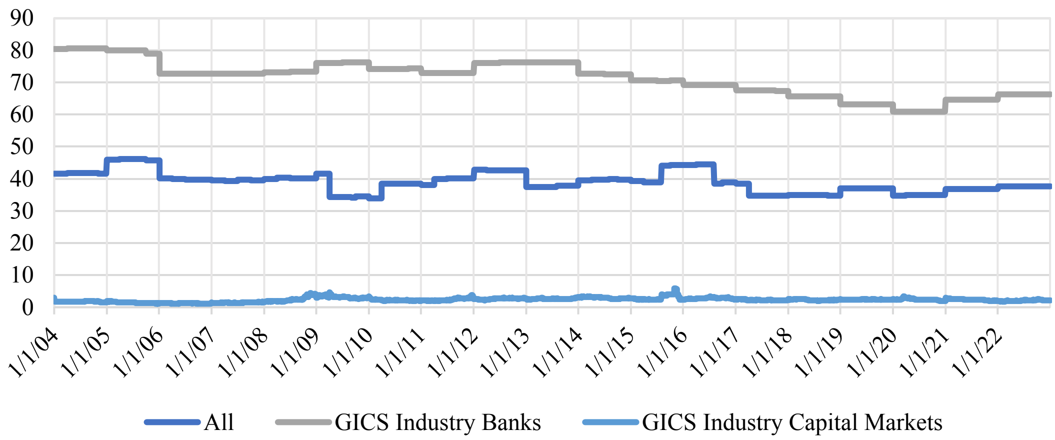
Figure 27: *CRISK of Largest Companies by Market Capitalization*



This figure displays CRISK of 5 largest companies by market capitalization as of 31/12/2022 in billion euros.
Source: Own illustration

8.10.2. CRISK by Industry

Figure 28: *Debt-to-Capital Ratio by Industry*

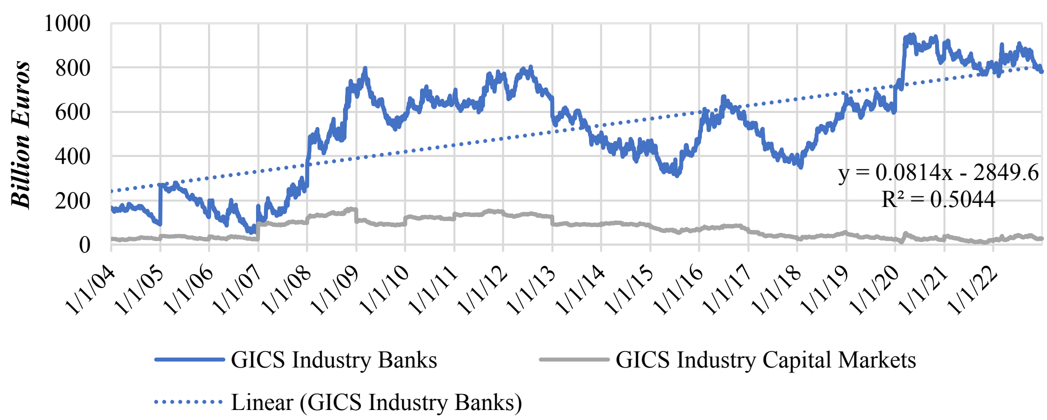


Source: Own illustration

Aggregate CRISK by Industry

Figure 29 illustrates the evolution of the $\Sigma CRISK$ over the observation period, disaggregated by industry. This visual representation highlights that throughout the observation period, the $\Sigma CRISK$ associated with the industry *Banks* is consistently higher than that of Capital Markets. Figure 29 also highlights that $\Sigma CRISK$ for banks has a positive trend. The trend coefficient of 0,081, estimated using a linear OLS regression, is slightly higher than the coefficient estimated for $\Sigma CRISK$ of the entire dataset (0,0742), as discussed in Section 4.3.1.

Figure 29: *Aggregate CRISK by Industry*



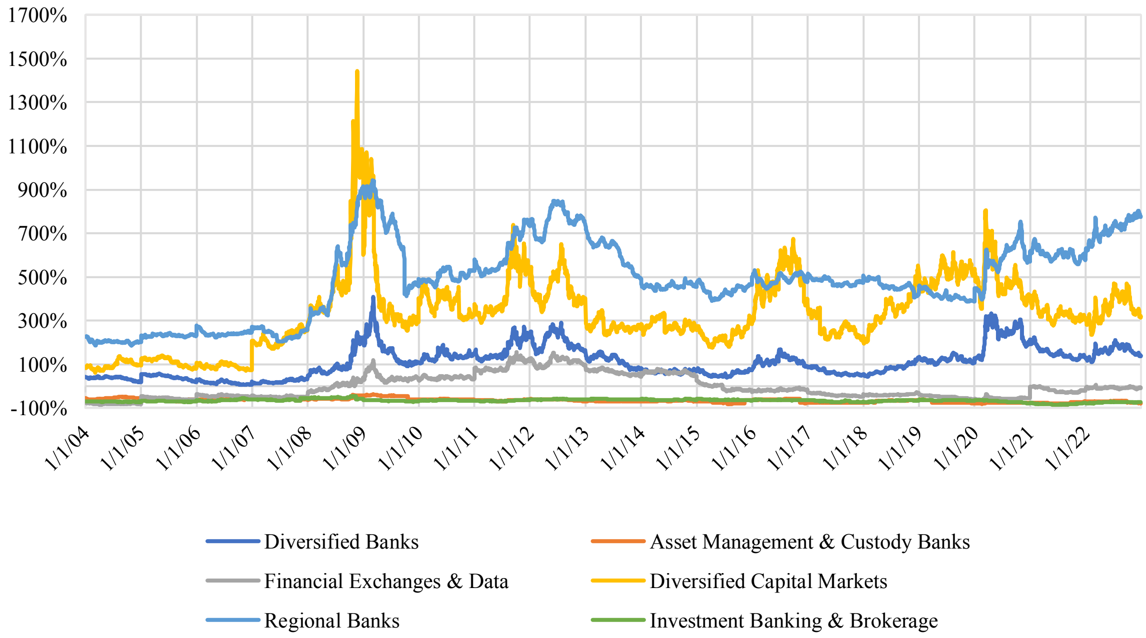
Source: Own illustration

Table 34: *Average Ratio of CRISK to MV by Sub-Industry*

Average	Aggregate MV	Aggregate CRISK	% of MV
Diversified Banks	538,73	510,06	***94,68%***
Regional Banks	2,87	13,75	***479,39%***
Asset Management & Custody Banks	25,82	-18,04	***-69,86%***
Diversified Capital Markets	31,91	93,30	***292,37%***
Financial Exchanges & Data	18,09	-2,65	***-14,63%***
Investment Banking & Brokerage	2,91	-2,03	***-69,78%***

This table displays average aggregate MV and ΣCRISK by sub-industry in billion euros.
% of MV *= Share of ΣCRISK relative to aggregate MV*
Source: Own calculation

Figure 30: *Share of Aggregate CRISK to Aggregate MV by Sub-Industry*

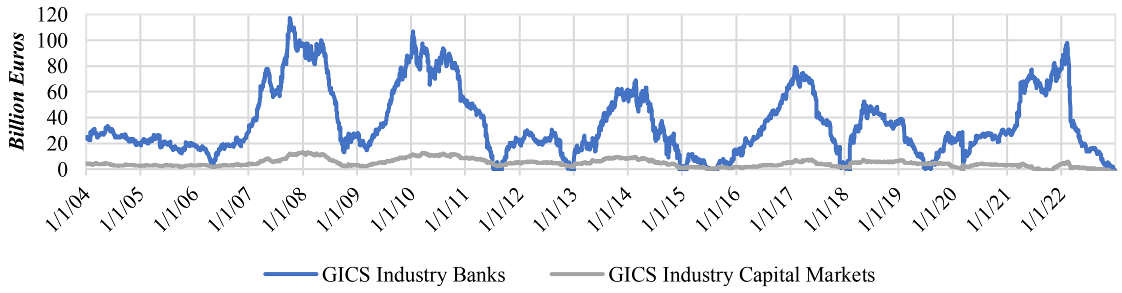


Source: Own illustration

Aggregate MCRISK by Industry

Figure 31 illustrates the evolution of the $\Sigma MCRISK$ over the observation period, disaggregated by industry.

***Figure 31**:Aggregate MCRISK by Industry*



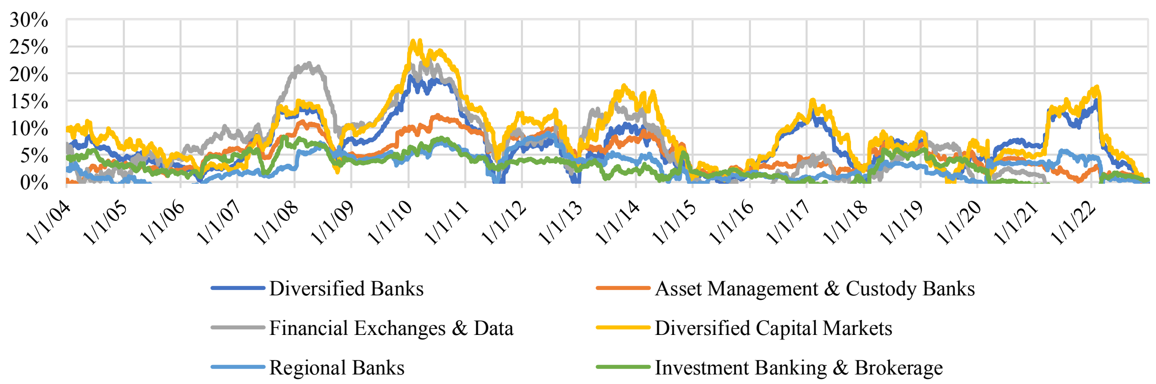
Source: Own illustration

***Table 35:** Average Ratio of MCRISK to MV by Sub-Industry*

Average	**Aggregate MV**	**Aggregate MCRISK**	**% of MV**
Diversified Banks	538,73	35,77	***6,64%***
Regional Banks	2,87	0,07	***2,48%***
Asset Management & Custody Banks	25,82	1,04	***4,03%***
Diversified Capital Markets	31,91	2,82	***8,84%***
Financial Exchanges & Data	18,09	0,67	***3,70%***
Investment Banking & Brokerage	2,91	0,04	***1,47%***

This table displays aggregate MV and $\Sigma MCRISK$ in billion euros.
***% of MV** = Share of $\Sigma CRISK$ relative to aggregate MV*
Source: Own calculation

***Figure 32:** Share of Aggregate MCRISK to Aggregate MV by Sub-Industry*

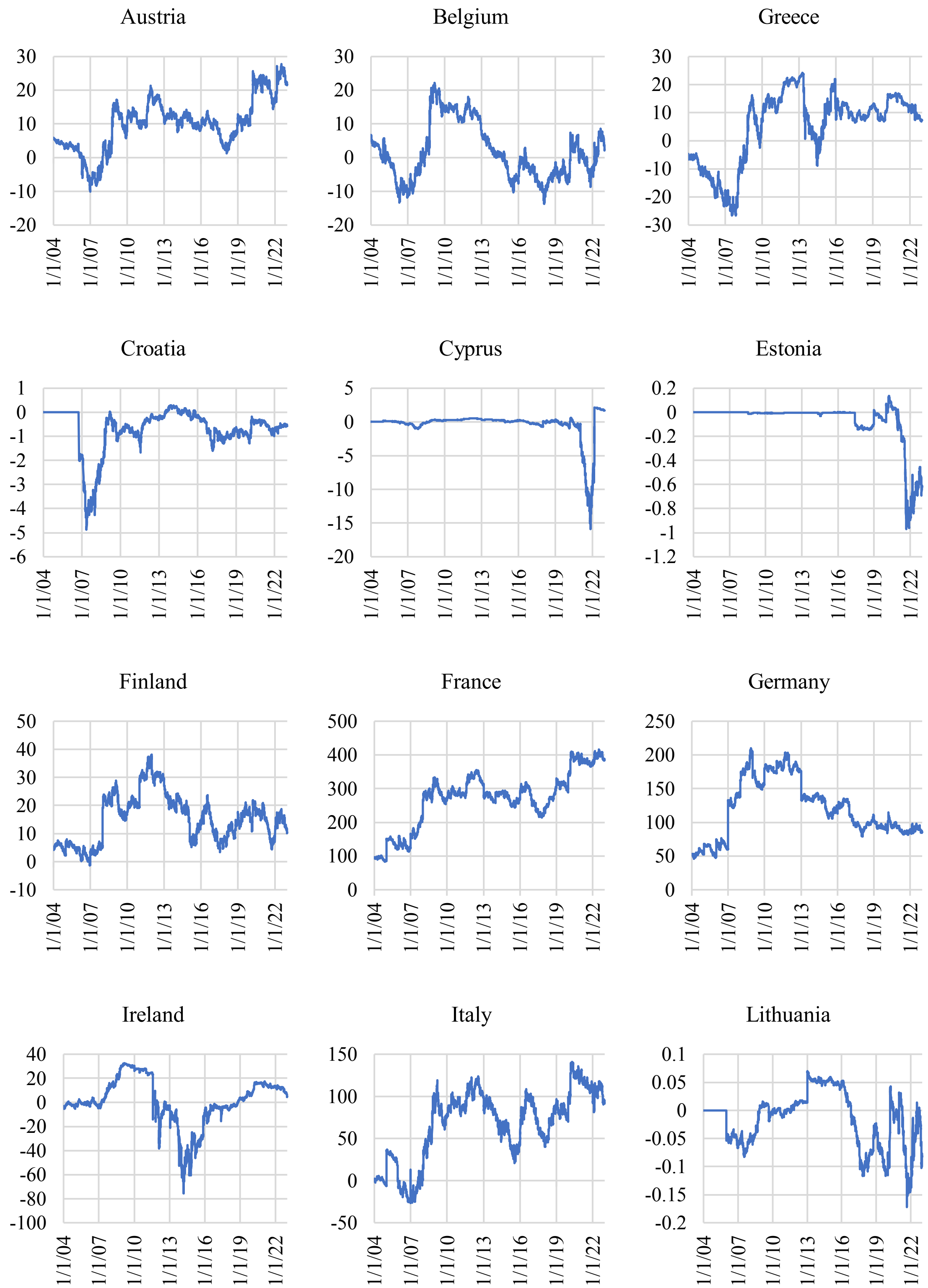


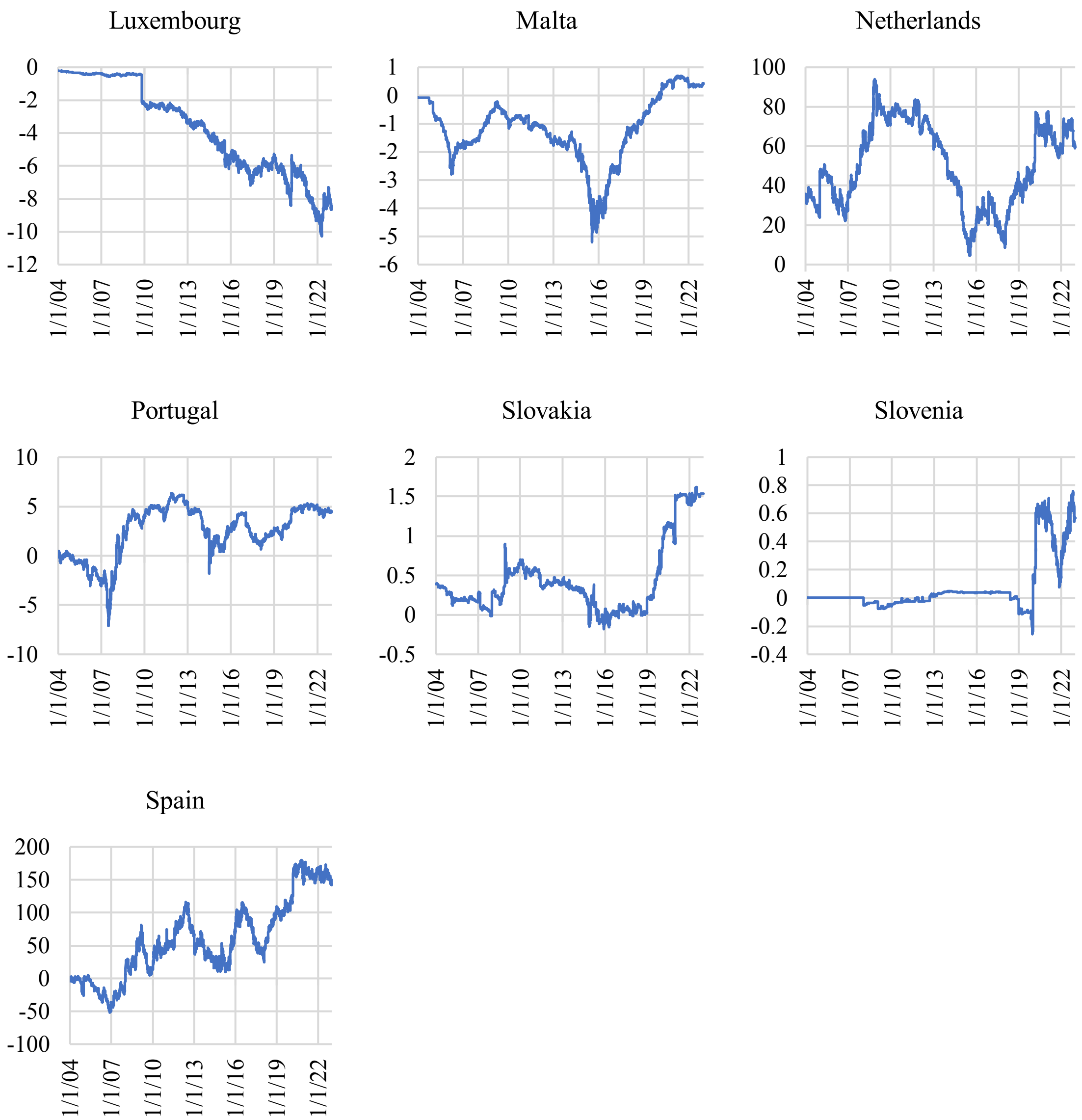
Source: Own illustration

8.10.3.CRISK by Country

Aggregate CRISK by Country

Figure 33: *Aggregate CRISK by Country (Billion Euros)*

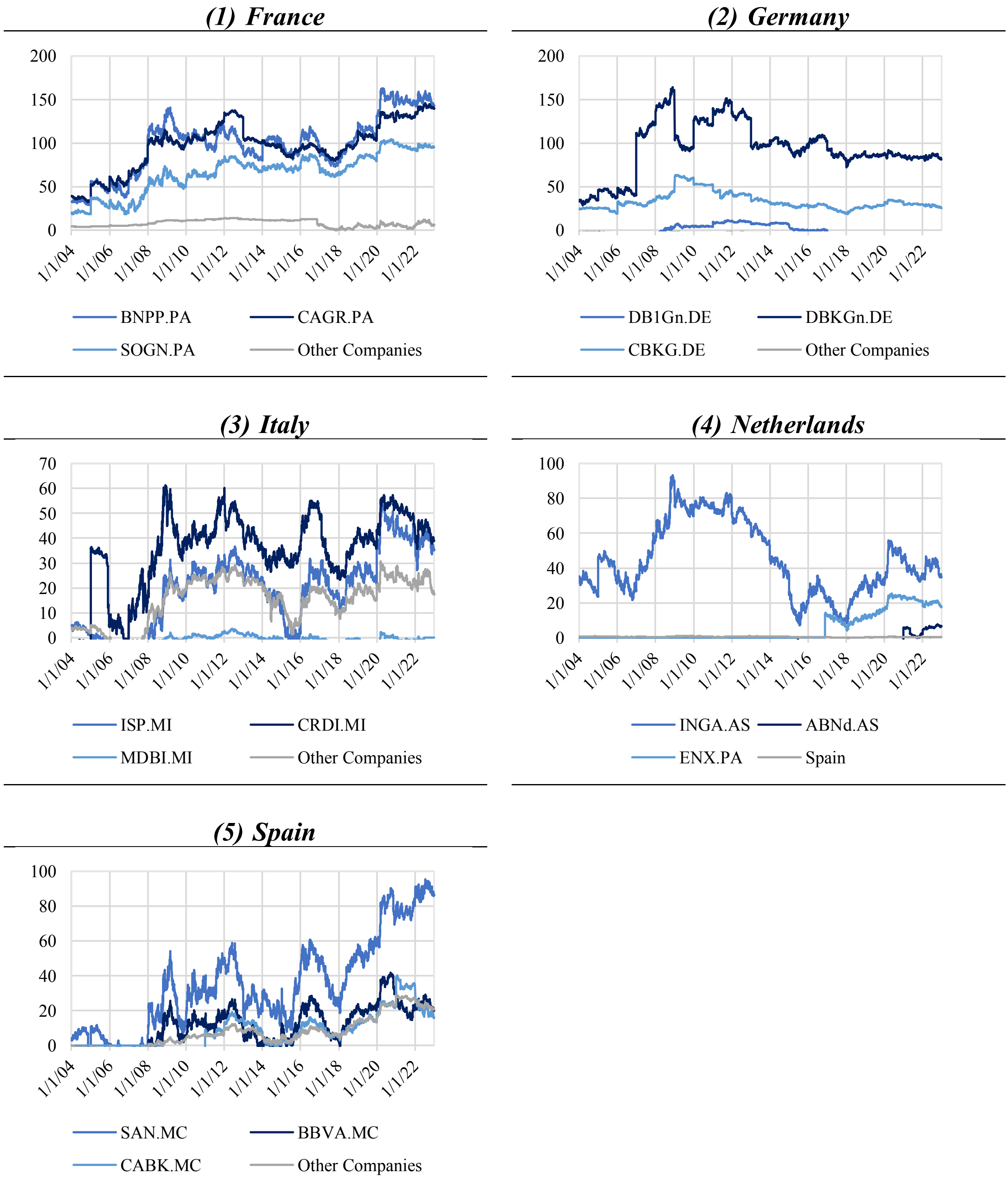




Source: Own illustration

CRISK of individual companies of top 5 countries

Figure 34: *Individual CRISK of Top Companies in Top Countries (Billion Euros)*

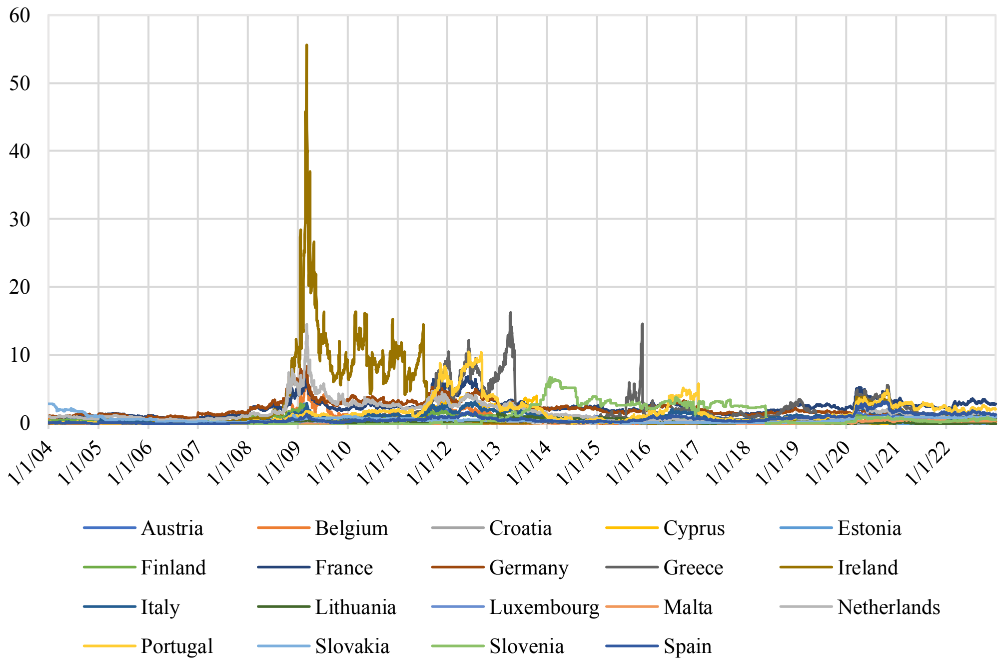


These graphs show the time-series development of CRISK in billion euros.

Source: Own illustration

Ratio of Aggregate CRISK relative to Aggregate MV by Country

Figure 35: *Ratio of Aggregate CRISK to Market Capitalization by Country*

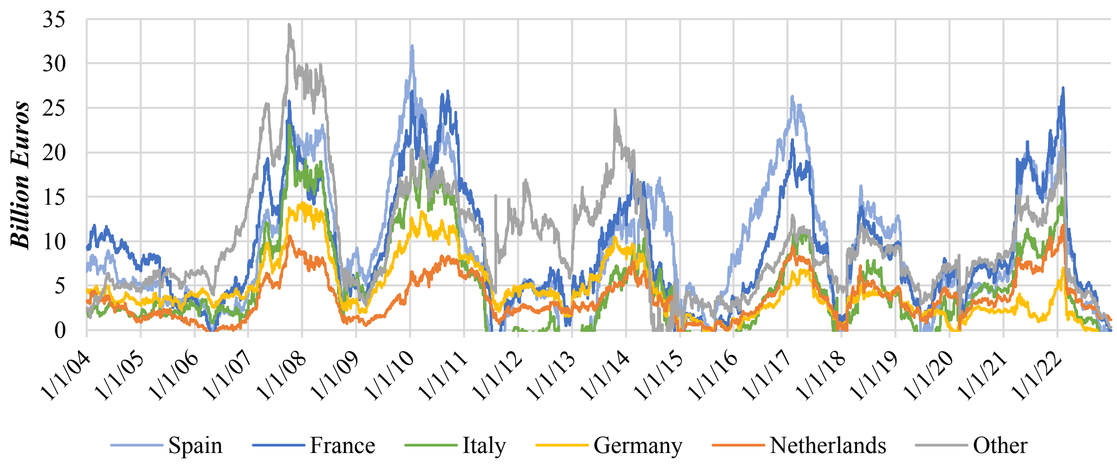


The values are truncated at zero.

Source: Own illustration

Aggregate MCRISK by Country

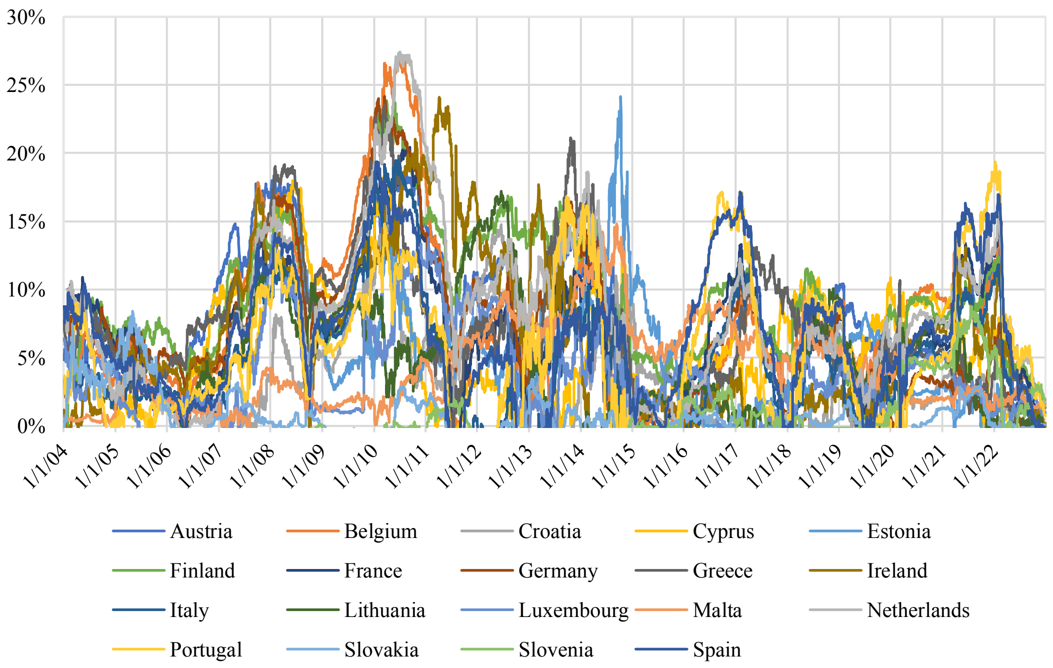
Figure 36: *Aggregate Marginal CRISK by Country*



The values are truncated at zero.

Source: Own illustration

Figure 37: *Ratio of MCRISK to Market Capitalization by Country*



The values are truncated at zero

Source: Own illustration

8.11. Marginal CRISK and Natural Disasters

Table 36: *Regression Marginal CRISK on DMG*

Regression Marginal CRISK	***Coefficients***	***Std Error***	***t Stat***	***P-value***
Intercept	33,7423	6,9617	4,8469	0,0002
DMG	7873,0086	5743,8742	1,3707	0,1883

Source: Own calculation

Table 37: *Correlation Marginal CRISK and DMG*

	Annual Average Marginal CRISK	***Total Damages as % of total GDP***
Annual Average Marginal CRISK	1	
Total Damages as % of total GDP	0,3155	1

*Significance levels: *** p<0,01, ** p<0,05, * p<0,1*

Source: Own calculation

8.12. Climate Policy Shock Event Study

8.12.1. Methodology

To assess the impact of exogenous shocks on the return of the Stranded Asset Portfolio, an event study method is following the market model approach of Brown & Warner (1985), where the abnormal return (AR) and the cumulative abnormal return (CAR) are calculated using an OLS Market Model. During the estimation window, which spans from t= -365 days before the event date to t=-31 days, the expected daily return $E(r_{CF_{Str},t})$ of the Stranded Asset Portfolio is estimated using the OLS market model as follows, using the daily return of the MSCI EMU Index as a proxy for market return $r_{MKT,t}$:

(20) $$E(r_{CF_{Str},t}) = \hat{\alpha} + \hat{\beta} \times r_{MKT,t}$$

Source: Brown & Warner (1985)

To estimate the alpha ($\hat{\alpha}$) and beta ($\hat{\beta}$) parameters, an OLS regression is performed of all observations within the estimation period, with the return of the Stranded Asset Portfolio as the dependent variable and the return of the market index as the independent variable:

(21) $$r_{CF_{Str},t} = \alpha + \beta \times r_{MKT,t} + \varepsilon_t$$

Source: Brown & Warner (1985)

In the event window spanning from T-30 days before the event to T+30 days after the event, the abnormal return (AR) is calculated as:

(22) $$AR_{CF(Str),t} = r_{CF_{Str},t} - E(r_{CF_{Str},t}) = r_{CF_{Str},t} - (\hat{\alpha} + \hat{\beta} \times r_{MKT,t})$$

Source: Brown & Warner (1985)

Next, the cumulative abnormal return (CAR) from t to T is calculated as follows:

(23) $$CAR(t_0, T) = \sum_{t=t_0}^{T} AR_{Str,t}$$

Source: Brown & Warner (1985)

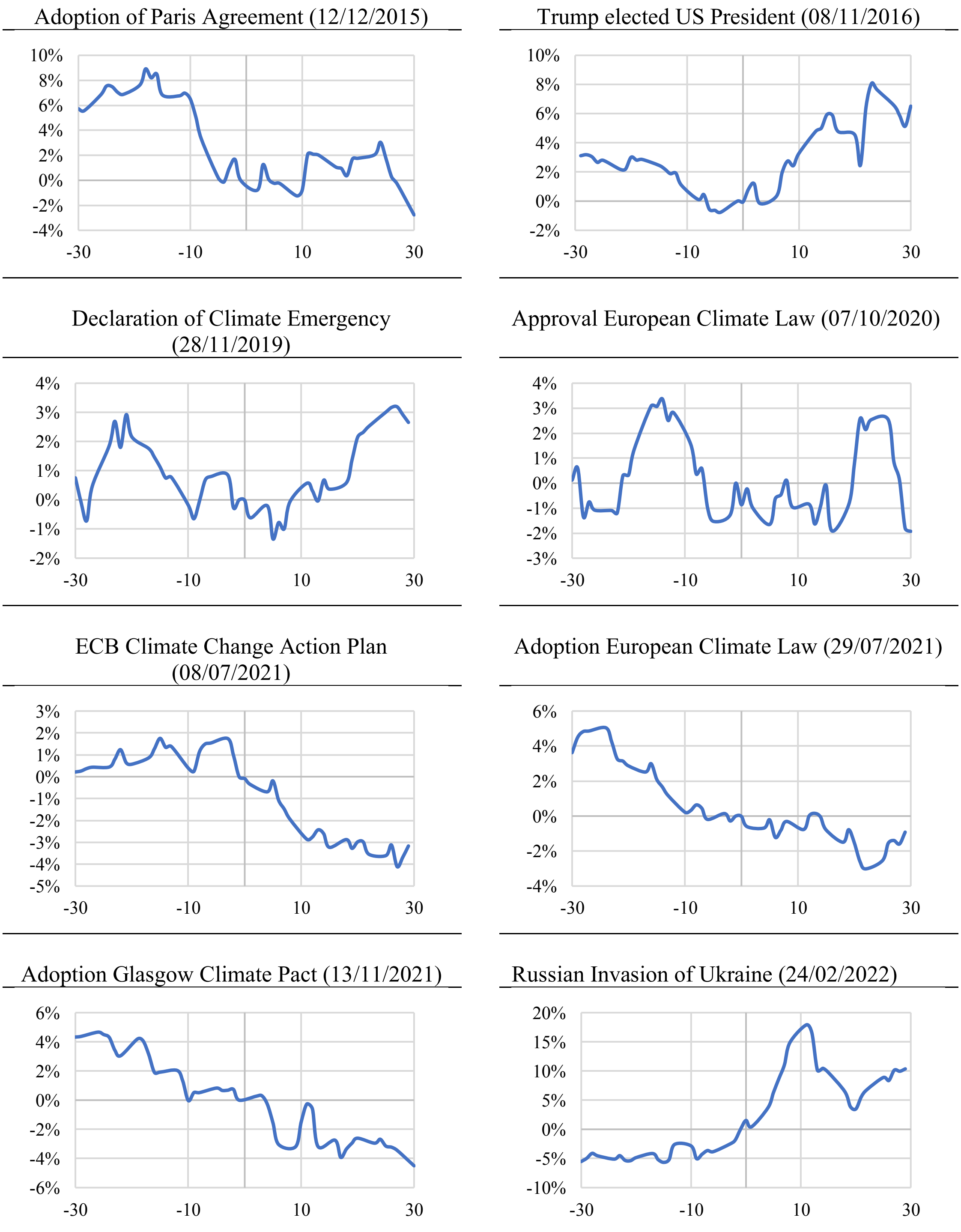
The CAR is calculated for three different event window sizes:

1. $CAR(t_{-30}, t_{30})$: Includes the entire event window, from 30 days before the event to 30 days after the event, with the aim to explore potential market expectations and trends related to the event.
2. $CAR(t_0, t_7)$: In this scenario, the analysis focuses on immediate market reactions and short-term effects by examining the event window from the event date to seven days after the event (T+7).
3. $CAR(t_0, t_{30})$: This calculation focuses on the medium-term abnormal return by analyzing the event window from the event date to 30 days after the event.

To evaluate the statistical significance of the abnormal returns, two t-tests are performed:
The first test examines the null hypothesis (H0) that the average abnormal return in the event window is equal to zero (H0: $\overline{AR}$ = 0), following the approach proposed by Brown & Warner (1985). The alternative hypothesis (H1) states that the cumulative abnormal return is not equal to zero (H1: AR ≠ 0). The test is performed for the average abnormal return in the event window. A normal distribution is assumed, and the test is performed for $AR(t_0, t_{30})$.
The second test examines the null hypothesis that the event has no effect on the changes in the return of the Stranded Asset Index, implying that the cumulative abnormal return is zero (H0: CAR = 0). The alternative hypothesis (H1) states that the cumulative abnormal return is not equal to zero (H1: CAR ≠ 0). This hypothesis is tested for $CAR(t_{-30}, t_{30})$, $CAR(t_0, t_7)$, and $CAR(t_0, t_{30})$, assuming a normal distribution.

8.12.2. Event Study Results

Figure 38: *Event Study Results – 30-Day CAR Graphs*



These graphs show the 30 days cumulative abnormal return (CAR) following the presented events. The x-axis depicts the number of days from the event date, while the y-axis shows the CAR in percentage.