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DYNAMIC INTERDEPENDENCE AMONG NORDIC STOCK MARKETS: THE ROLE OF CLIMATE RISKS

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ABSTRACT:

This study investigates the dynamic return interdependence among Nordic and major global stock markets, as well as the underlying determinants of this connectedness. Applying the Quantile Vector Autoregression (QVAR) framework, this study analyzes twenty-five years of daily data (2000–2024) covering Finland, Sweden, Denmark, and Norway, alongside benchmark indices from the U.S., Europe, Japan, and China. The results show that the level of interdependence within the network is substantially strong at the median quantile, reflecting a high degree of return transmission among these countries. Moreover, return spillovers intensify significantly during both extreme downturns and rallies, indicating that the structure of market linkage is highly state-dependent and asymmetric. The study further finds that peaks in connectedness coincide with major global events such as the Global Financial Crisis, Brexit, the COVID-19 pandemic, and the Russia–Ukraine conflict. At each market level, the U.S., Europe, and Sweden consistently act as net transmitters of shocks, while Denmark and Asian markets typically serve as net receivers. Finland often acts as a transmitter but shifts to a net receiver during periods of crisis. Norway, meanwhile, exhibits relative resilience, maintaining minimal directional connectedness across different market states. Furthermore, the study examines the impact of climate risks and other uncertainty factors on market integration. Ordinary Least Squares (OLS) regressions are conducted using the Total Connectedness Index (TCI) across different quantile levels as the dependent variables. The results indicate that physical risks do not exhibit statistically significant effects within the multivariate framework. In contrast, transition risk and market sentiment emerge as significant drivers of return connectedness, particularly under normal and bearish market conditions. Economic policy uncertainty contributes positively to integration during stable and bullish periods. Likewise, geopolitical risk exerts a negative influence on market linkages. These findings emphasize the importance of incorporating climate transition risks, investor sentiment, and political uncertainty into portfolio construction and risk assessment frameworks. Furthermore, the study points out the value of quantile-based approaches in capturing the nonlinear and regime-dependent nature of financial market interdependence, particularly during turbulent times.

KEYWORDS: Interdependence, connectedness, Nordic stock markets, climate risks

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Abbreviations

CPU	Climate Policy Uncertainty
DICE	Dynamic Integrated Climate-Economy model
EM	Emerging markets
EMH	Efficient Market Hypothesis
EPU	Economic Policy Uncertainty
ESG	Environmental, Social, and Governance
GARCH	Generalized Autoregressive Conditional Heteroskedasticity
GFEVD	Generalized Forecast Error Variance Decomposition
GHG	Greenhouse gases
IPCC	Intergovernmental Panel on Climate Change
MCCC	Media climate change concerns index
MPT	Modern Portfolio Theory
NGFS	Network for Greening the Financial System
PRI	Physical Risk Index
QVAR	Quantile Vector Autoregression
SCC	Social Cost of Carbon
SRI	Socially responsible investing
TCFD	Task Force on Climate-related Financial Disclosures
TRI	Transition Risk Index
TVP-VAR	Time-Varying Parameter Vector Autoregression

1 INTRODUCTION

1.1 Background and motivation

In early April 2025, U.S. President Donald Trump announced reciprocal tariffs on all imports, reigniting global concerns over trade protectionism and triggering widespread declines in global stock markets. This event highlights the growing complexity and fragility of financial systems in an era marked by geopolitical uncertainty, fluctuating investor sentiment, and systemic risks. Under such conditions, financial markets are not only exposed to traditional macroeconomic shocks but also to high-impact, unpredictable phenomena - often referred to as black swan events - such as the 2008 financial crisis, the COVID-19 pandemic, and the ongoing Russia-Ukraine conflict. These disturbances reinforce the connectedness among global financial markets and underline how investor behavior is highly responsive to external shocks.

The concept of market interdependence - the extent to which financial markets move together and influence one another through co-movements in returns and volatility transmission - has gained renewed attention. Financial markets no longer operate in isolation; instead, they exhibit complex structural and dynamic linkages shaped by globalization, capital mobility, and investor sentiment. The relevance of understanding this interdependence has grown significantly, particularly since the 1987 stock market crash and even more so in the aftermath of the 2007–2009 global financial crisis. These events highlighted how financial shocks can rapidly spread across borders, prompting a surge in empirical research into the extent and drivers of market integration. Studies on interdependence span a wide range of asset classes, including equities, bonds, commodities, and foreign exchange, and encompass diverse regional and global markets. A distinction is drawn between interdependence and contagion: while contagion refers to excessive co-movements during crisis periods compared to a benchmark period, interdependence reflects a more stable, continued high level of financial linkages under normal market conditions (Forbes & Rigobon, 2002). Interdependence has become more pronounced with the acceleration of financial globalization, as local shocks, whether macroeconomic or firm-specific, now have the potential to trigger instability across broader markets.

Amid these challenges, climate change has emerged as a systemic and multidimensional risk with profound financial implications. Nordhaus (2019) emphasizes the economic implications of climate change, arguing that it represents the most critical externality humanity confronts. Since the Industrial Revolution, the accumulation of carbon dioxide (CO_2) and other greenhouse gases (GHG), primarily driven by human activities, has led to climate change. One of the most critical consequences of this trend is the steady rise in average global temperatures, which, according to the IPCC (2023), will likely exceed +2°C within this century. This warming intensifies the frequency and severity of extreme weather events, accelerates sea-level rise, and contributes to biodiversity loss. In response, economies worldwide are undergoing a necessary but complex transition toward low-carbon development, characterized by the phasing out of fossil fuels and widespread adoption of clean energy technologies. The transition is expected to restructure some key sectors and to introduce significant structural shifts in macroeconomic dynamics and financial market behavior.

Climate risk, defined as the potential adverse impacts of climate change on human and ecological systems, has been considered a critical dimension in assessing market stability and interdependence. Climate risk is typically categorized into two categories: physical risks and transition risks. According to TCFD (2017), physical risks, including acute and chronic risks, arise from event-driven or long-term shifts in climate patterns. On the other hand, transition risks, including policy and legal, technology, market, and reputation risks, result from the economic, technological, policy, and societal shifts required to achieve net-zero emissions. A growing body of literature has explored how climate risks are transmitted through financial systems. While some studies investigate how climate risks propagate through the financial system (Lorente et al., 2023; Mao et al., 2023; Zhao et al., 2023), numerous others focus on their impact on stock market connectedness. Among the latter, several use ESG or climate change indices to assess how interdependence evolves under varying market conditions (Z. Umar et al., 2020; Gao et al., 2022; Hoque et al., 2024; Wan et al., 2024). Others adopt a two-step approach: calculate the network connectedness over time and then analyze the effects of climate risk and other control variables on the level of connectedness (Urom & Ndubuisi, 2023; Guo et al., 2024; Basher & Sadorsky, 2024; Cao, 2025).

The Nordic countries, including Sweden, Finland, Denmark, Norway, and Iceland, are well-positioned to examine the relationship between climate risks and financial market interdependence. Parts of the Nordic territories lie within or near the Arctic Circle, among the areas most severely affected by climate change. The Arctic is warming at a rate two to three times faster than the global average - a phenomenon known as Arctic amplification. While the implications of this accelerated warming remain relatively underexplored, the region has already experienced a marked increase in the frequency and intensity of extreme weather events, signaling significant ecological and geopolitical transformations. Due to their geographic proximity and partial inclusion in this rapidly warming region, the Nordic countries are particularly vulnerable to both physical and transition climate risks. At the same time, these countries are widely recognized for their leadership in sustainability, climate governance, and green innovation. Each has implemented ambitious climate goals aligned with the Paris Agreement (2015), invested heavily in renewable energy technologies, and promoted environmentally responsible corporate practices. However, their open economies and highly integrated financial systems expose them to cross-border spillovers and evolving climate-related financial risks. Moreover, the Nordic markets are tightly connected through trade, capital flows, and coordinated policy frameworks. As a result, shocks, whether economic, policy, or environmental-related, in one national market likely swiftly propagate across others, amplifying regional financial volatility.

The interdependence of European and Nordic stock markets has been documented in prior research. Dengjun (2015) identifies both long- and short-term linkages among Nordic markets. More recent studies have adopted connectedness approaches to analyze market interdependence, including during turbulent periods. These studies show that financial and geopolitical shocks increase volatility spillovers, with developed markets often acting as key transmitters (Mensi et al., 2018; Su, 2020; Li, 2020; Z. Umar et al., 2024; Lang et al., 2024). However, limited attention has been paid to the interdependence among Nordic markets and the dynamics of connectedness under different market conditions. Furthermore, few studies have examined how climate risks, particularly their physical and transition dimensions, affect market connectedness. Therefore, this thesis aims to address these gaps by examining the dynamics of return connectedness among Nordic stock markets and assessing the impact of climate risks on this linkage.

1.2 Research objectives

The primary objectives of this thesis are to investigate the interdependence of returns among Nordic and major global stock markets and to assess the impact of perceived climate risks on this connectedness. In particular, it examines return connectedness among four Nordic stock markets (Finland, Sweden, Denmark, and Norway), while also considering the impact of other major global stock markets on this network (the U.S., European, Japan, and China). The analysis employs the Quantile Vector Autoregression (QVAR) approach (Chatziantoniou et al., 2021; Ando et al., 2022) to explore whether connectedness intensifies during different phases of market conditions, such as boom and bust periods. Furthermore, the study identifies the role of each market in the network as a shock transmitter or receiver. It explores how these roles evolve across different economic states, thereby investigating how shocks are transmitted throughout the financial system.

To quantify the impact of climate risks on the spillover connectedness of the network, similar to prior studies that employ text analysis to measure climate risks, this study uses the Physical Risk Index (PRI) and the Transition Risk Index (TRI) developed by Bua et al. (2024), which reflect innovations in media-based perceptions of physical and transition climate threats. By incorporating these variables, the study aims to evaluate how each type of climate risk influences the structure and intensity of financial market spillovers.

Building upon the above objectives, this thesis seeks to address the following research questions:

- How does return interdependence evolve among Nordic and major global stock markets across different market conditions?
- Which markets act as shock transmitters and which as receivers within the network, and how do their roles vary under different market regimes?
- How do physical and transition climate risks affect the connectedness among stock markets?

1.3 Contribution

This thesis contributes to the literature in several ways:

First, examining the return interdependence among Nordic markets enhances our understanding of stock market linkages. Given the region's high degree of financial integration and exposure to climate-related risks, analyzing these linkages provides valuable insights into how shocks propagate across markets.

Second, by applying QVAR connectedness measures and network analysis, the study captures the dynamics of return spillovers across various quantiles, offering a more refined view of how interdependence evolves under different market conditions.

Third, the thesis incorporates climate risks, categorized into physical and transition risks, to evaluate their impacts on stock market connectedness. By separating these dimensions, the study assesses the relative magnitude and significance of each, contributing to a deeper understanding of climate-related financial vulnerability.

Ultimately, the findings have important policy relevance, providing evidence-based insights for investors and policymakers concerned with the intersection of market integration and climate-related risks.

1.4 Thesis structure

The thesis is organized as follows:

Part 1 introduces the study by presenting the background and motivation, research objectives, key contributions, and an overview of the thesis structure.

Part 2 reviews theoretical foundations relevant to the study.

Part 3 presents prior studies on stock market interdependence and climate risks, as well as presents hypotheses.

Part 4 outlines the data sources, variable construction, and methodology employed in the analysis.

Part 5 presents the descriptive statistics, empirical tests, and findings, followed by a discussion of the results.

Part 6 summarizes the main findings, offers practical recommendations, highlights limitations, and proposes directions for future research.

2 THEORETICAL BACKGROUND

This section reviews key theoretical frameworks that have shaped the understanding of market risk and returns, portfolio construction, and financial market interdependence. It also addresses the growing influence of sustainable investing, climate finance, and climate risks in contemporary finance theory.

2.1 Modern Portfolio Theory and Efficient Market Hypothesis

2.1.1 Modern Portfolio Theory (MPT)

The Modern Portfolio Theory (MPT), developed by Markowitz (1952), is a foundational framework in investment. The theory assumes that investors are risk-averse, meaning they prefer to minimize risk while seeking to maximize returns. Therefore, the primary objective of rational investors, according to MPT, is to maximize expected return for a given level of risk, or equivalently, to minimize risk for a given expected return. The theory introduced the concepts of mean-variance optimization and the efficient frontier, providing a quantitative approach for constructing optimal investment portfolios. The theory also emphasizes the benefit of diversification - the idea that a portfolio consisting of uncorrelated or low-correlated assets can reduce overall risk.

MPT shifts the focus from evaluating individual assets in isolation to viewing the portfolio as an integrated whole. However, the theory is built upon several simplifying assumptions, including normally distributed asset returns, frictionless markets, and rational investor behavior. These assumptions have been increasingly challenged by empirical evidence and alternative models, particularly those in behavioral finance, which acknowledge market imperfections, cognitive biases, and deviations from rationality in investor decision-making. Despite its limitations, MPT provides a valuable framework for understanding how investors incorporate risk considerations into portfolio management, particularly in response to rising uncertainty or market volatility.

2.1.2 Efficient Market Hypothesis (EMH)

The Efficient Market Hypothesis (EMH), popularized by the work of Fama (1970), argues that all available information is entirely and immediately reflected in stock prices, making it impossible to consistently earn excess returns through information-based trading. Fama categorized market efficiency into three levels: weak-form efficiency, semi-strong form, and strong-form efficiency. For the efficient market theory to be completely accurate, EMH assumes rational investors, frictionless markets, and instantaneous price adjustments, providing a theoretical basis for passive investment strategies.

While early studies supported the unpredictability of returns, subsequent research uncovered various market anomalies, such as momentum, size, and value effects, that challenge the assumptions of the EMH. Furthermore, behavioral finance criticizes EMH by highlighting the role of investor psychology and cognitive biases in generating persistent mispricings. Empirical observations during financial bubbles and crises have demonstrated that markets are not always entirely rational and may fail to accurately price assets. Moreover, emerging sources of systemic risk, including climate change, geopolitical instability, and economic uncertainty, raise further questions about the market's ability to incorporate all relevant information promptly and efficiently.

2.2 Behavioral Finance

At the core of behavioral finance is the recognition that investors do not always process information in a fully rational or objective manner. Instead, they are subject to bounded rationality, a concept introduced by Simon (1955), which suggests that individuals operate under cognitive limitations when making decisions. These limitations cause investors to rely on mental shortcuts, or heuristics, to simplify complex financial information. While heuristics can be helpful in routine situations, they often lead to systematic errors - commonly called behavioral biases - affecting investment decisions and market outcomes. One of the most influential foundations of behavioral finance is Prospect Theory, developed by Kahneman and Tversky (1979). Unlike expected utility theory, which assumes consistent risk preferences, prospect theory reveals that people evaluate outcomes based on gains and losses relative to a reference point and are generally loss averse - they perceive the pain of a loss as greater than the pleasure from a comparable gain. This tendency explains why investors may hold on to losing stocks too long (the disposition effect) or panic-sell during downturns. Another well-documented bias is overconfidence, which leads individuals to overestimate their predictive abilities or control over outcomes.

During the 1980s, researchers began applying psychological insights directly to finance. Richard Thaler, a key figure in behavioral economics, introduced concepts such as mental accounting (Thaler, 1980, 1985) and the endowment effect (Kahneman et al., 1990), which explained how investors irrationally value and categorize wealth. Besides, the study of De Bondt & Thaler (1985) investigates overreaction in stock returns. These early empirical works exposed inconsistencies in the EMH. They showed that asset prices often deviated from fundamental values due to behavioral patterns, such as short-term memory, regret aversion, and biased beliefs. The field continued to expand with the contribution of scholars such as (Barberis et al., 1998), who advanced theories of investor sentiment, arguing that stock prices could be influenced by systematic psychological factors rather than pure fundamentals. Their model explained anomalies like momentum and reversals using behavioral concepts. Similarly, the study of Lakonishok et al. (1994) demonstrated the value anomaly, where value stocks systematically outperformed growth stocks, contradicting predictions of rational asset pricing models. These studies established behavioral finance within the academic and professional finance communities. Behavioral finance gained widespread attention in the 2000s, particularly following the bursting of the dot-com bubble and later the global financial crisis. In his influential book, Robert Shiller argued that speculative bubbles could be better explained by investor psychology and herd behavior than by fundamentals (Shiller, 2000)The Nobel Prize was awarded to Kahneman in 2002 for his work on decision-making and later to Thaler in 2017, marking the recognition of behavioral economics as a cornerstone of modern finance.

In recent years, behavioral finance has evolved by integrating big data analytics, sentiment measurement tools, and other factors such as sustainability and social influences. A significant contribution to this area was made by Baker & Wurgler (2007), who formalized the concept of investor sentiment as a systematic, measurable force in financial markets. They constructed a composite sentiment index using market-based indicators and showed that high sentiment levels are linked to future mispricing, particularly in stocks that are difficult to value and arbitrage. Their work proved that sentiment is not merely noise but a significant explanatory variable in asset pricing. Moreover, the development of investor sentiment indices using social media and news analytics has enhanced the measurement of market mood in real time (Da et al., 2015). These sentiment measures are increasingly being used as behavioral factors in multi-factor asset pricing models, helping explain deviations from fundamentals in specific stocks or markets. Moreover, a growing body of literature explores how climate-related events such as natural disasters, extreme weather, or regulatory announcements can trigger heightened investor sentiment, resulting in synchronized market responses. Similarly, ESG narratives and sustainability-oriented preferences are found to shape investor choices. These developments underscore the expanding role of moral heuristics, environmental awareness, and sentiment-driven trading in financial markets.

2.3 Sustainable Investing

Sustainable investing, sometimes referred to as socially responsible investing (SRI) or environmental, social, and governance (ESG) investing, is an investment approach that integrates ESG factors into portfolio selection and management to achieve long-term financial returns while promoting sustainable development. It is grounded in the broader framework of sustainability, which incorporates three interconnected dimensions: economic, social, and environmental factors (Figure 1). The conceptual origins of this framework and the moment it gained widespread acceptance remain unclear (Purvis et al., 2019). Closely related to the concept of sustainability is sustainable development, defined as the development that meets the needs of the present without compromising the ability of future generations to meet their own needs. This notion serves as a guiding principle at the global, national, organizational, and individual levels. Sustainable development seeks to harmonize economic growth, environmental conservation, and social equity. The nexus between sustainability and finance is a growing area of study, attracting increasing investigations on the role of finance in promoting a sustainable society.

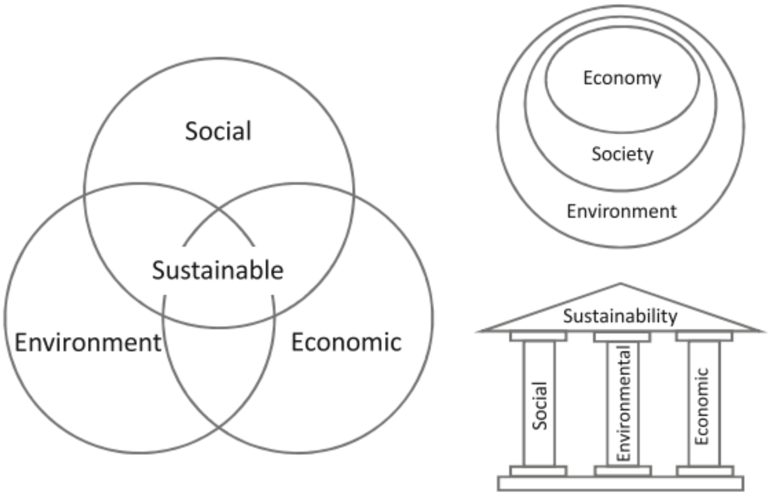

Figure 1. Three visual representations of Sustainability and its three dimensions (Purvis et al., 2019)

The concept of sustainable investing dates as far back as the 18th century, with religious groups like the Quakers and Methodists avoiding "sin" industries such as alcohol, tobacco, and weapons. The modern form of SRI emerged in the 1960s and 1970s. This era witnessed the rise of greater social and environmental awareness, leading to investment strategies guided by ethical and moral considerations. SRI during this era was primarily defined by negative screening, such as excluding companies involved in controversial sectors or practices. Famous historical examples include boycotts and divestments aimed at South African firms during apartheid and investment restrictions during the Vietnam War. The Pax World Balanced Fund, launched in 1971, is widely recognized as the first ethical mutual fund, established to help investors avoid companies linked to the production of Agent Orange. These movements paved the way for a generation of socially conscious investors seeking to affect social and political change.

By the late 1990s and early 2000s, the concept expanded with the formalization and rise of ESG factors, driven by growing awareness of corporate responsibility and the financial materiality of non-financial information. This shift featured a move from negative screening to positive selection of companies that demonstrate strong ESG performance. The term ESG gained widespread recognition following the release of the 2004 report, initiated at the request of the United Nations (UN), titled "Who Cares Wins." ESG standards have been developed in response to the growing worldwide demand for more sustainable and socially responsible investments. They are used to assess the sustainability and ethical practices of companies. These criteria help investors identify risks and opportunities that may not appear in traditional financial analysis. The launch of sustainability indices, such as the Dow Jones Sustainability Index in 1999, the first global sustainability benchmark, and the establishment of frameworks like the UN Principles for Responsible Investment (PRI) in 2006, provided a global framework for institutional investors to incorporate ESG into investment practices.

Recently, sustainable investing has gained momentum through policy support and alignment with global initiatives, such as the UN Sustainable Development Goals (SDGs) and the Paris Agreement (2015). The SDGs outline 17 interconnected goals that address environmental, social, and economic development, thereby laying the foundation for a more sustainable and equitable future. Meanwhile, the Paris Agreement tackles climate change by urging nations to implement measures that limit global warming to well below 2°C above pre-industrial levels. Consistent with these global efforts, ESG factors are increasingly used to assess risks and opportunities related to climate change, resource efficiency, and corporate governance. The environmental dimension of ESG encompasses critical issues, including climate change, greenhouse gas emissions, energy consumption, pollution, and natural resource management. The social dimension includes labor practices, human rights, employee well-being, diversity and inclusion, and community impact. The governance dimension focuses on corporate structures and practices, including board composition, executive compensation, shareholder rights, and ethical business conduct. Together, these pillars form a comprehensive framework for assessing the sustainability performance of firms and aligning financial decision-making with long-term societal goals. Investors adopt a range of sustainable investment strategies, guided by their values, regulatory expectations, and risk-return objectives. In some cases, environmental outcomes are prioritized over financial returns.

Despite its growing popularity, terminological ambiguity and inconsistency in ESG practices persist as a challenge within sustainable investing. Studies have shown that a lack of commonality in ESG definitions, characteristics, and standards has resulted in major rating agencies forming opposite conclusions on the same evaluated companies, with low agreement across providers (Billio et al., 2021). This heterogeneity affects how ESG is measured and the construction of investment universes and benchmarks, making it difficult for investors to compare firms or assess performance consistently. Nevertheless, sustainable investing continues to gain momentum due to increasing regulatory pressure, climate-related risks, and shifting investor preferences. More recently, the field has begun to intersect with behavioral finance and big data analytics, enabling the real-time measurement of sustainability sentiment and market reactions to ESG disclosures. Today, sustainable investing is a dynamic and fast-growing discipline, influencing asset allocation, regulatory policy, and corporate strategy worldwide. It reflects a paradigm shift in finance, where long-term performance, ethical responsibility, and environmental resilience are no longer mutually exclusive but integrated priorities.

2.4 Climate finance and climate risks

2.4.1 Climate finance

Climate finance refers to local, national, or transnational financing - drawn from public, private, and alternative sources of financing - that seeks to support mitigation and adaptation actions that will address climate change (UNFCCC - United Nations Framework Convention on Climate Change). It has emerged at the intersection of environmental economics, macroeconomics, and financial theory, with the need to address climate change as a systemic financial risk. Mitigation efforts aim to limit the causes of climate change by reducing greenhouse gas emissions. Meanwhile, adaptation strategies are designed to cope with the current and anticipated effects of climate change. Financial markets play a central role in the functioning of climate finance, by allocating capital toward low-carbon investments while deterring financing of carbon-intensive sectors. Markets also facilitate risk-sharing through instruments such as insurance, derivatives, and diversification strategies. Incorporating climate risk into valuation models and investment decisions enhances the financial system's resilience. Increasingly, financial institutions are embedding climate considerations into their governance, disclosure practices, and strategic planning processes.

Like other environmental problems, climate change constitutes a negative externality, where the harmful effects of greenhouse gas emissions are not borne by the emitters themselves but are instead imposed on society as a whole. Without intervention, firms and consumers lack sufficient incentives to reduce emissions, resulting in market failure. The foundational idea of pricing environmental externalities was first suggested by economist Arthur Pigou in 1912, who proposed taxing activities that generate harmful side effects, such as pollution. Although Pigou did not specifically address carbon dioxide emissions, his framework laid the theoretical foundation for contemporary concepts such as the Social Cost of Carbon (SCC). Furthermore, climate stability is understood as a global public good, non-excludable and non-rivalrous, leading to underprovision due to the free-rider problem. Since climate benefits are shared globally, individual countries often lack the incentive to invest unilaterally in mitigation or adaptation efforts. This challenge has prompted the development of international climate finance mechanisms to mobilize collective action. Public sector participation is essential, particularly in developing countries, to complement private investment and ensure an equitable and inclusive global response to climate change.

A pioneering figure in climate finance is William D. Nordhaus, who was awarded the Nobel Prize in Economics in 2018 for his foundational works since the 1970s regarding the interactions between climate change and the economy. Nordhaus developed Integrated

Assessment Models (IAMs) such as the DICE model, which integrated climate science with macroeconomic modeling to evaluate the trade-offs between economic growth and environmental protection. His work provided a theoretical foundation for climate policies, particularly by advocating for carbon pricing as an economically efficient corrective mechanism for greenhouse gas emissions. These early models primarily focused on identifying optimal climate mitigation strategies within deterministic settings, helping to formalize the pricing of climate externalities. More recent extensions of this literature incorporate uncertainty, risk, and nonlinearities to improve understanding of how climate change influences optimal policy choices and economic outcomes (Bhandary et al., 2021). The evolving financial economics literature now explores the implications of climate risks for asset pricing, expected returns, and portfolio construction, bridging a gap between climate science and financial market dynamics (Giglio et al., 2020). This growing body of research also examines how markets respond to climate-related information, including physical climate shocks and regulatory developments. Emerging topics such as investor sentiment, risk perception, and the pricing of climate-related events are gaining importance. Since beliefs significantly influence both the financing of innovative technologies aimed at climate mitigation and the valuation of assets exposed to climate change, understanding these beliefs is essential to the discussion of market efficiency in the context of pricing climate-related risks (Hong et al., 2020).

The field of climate finance has also been enriched by the integration of Environmental, Social, and Governance (ESG) factors into financial decision-making. Theoretical models now examine how investor preferences for sustainability, regulatory frameworks, and ESG-related performance influence capital flows and market outcomes (Giese et al., 2019). These developments indicate a shift toward long-term value creation that balances financial returns with environmental and social objectives. Models building on utility theory suggest that investors derive utility not only from financial gains but also from aligning their portfolios with ethical or environmental values, commonly referred to as non-pecuniary preferences. As a result, ESG is now viewed not merely as a tool for risk screening but as a strategic and forward-looking framework that directs capital toward more resilient, sustainable, and future-oriented business models, reinforcing the financial sector’s role in addressing systemic climate risks.

2.4.2 Climate risks

Climate risks are increasingly recognized as material financial risks with significant implications for asset pricing, portfolio management, and financial system stability. Climate risks are typically categorized into two main types: physical risks and transition risks. Physical risks, including acute and chronic risks, stem from the direct physical effects of climate change. Acute risks involve extreme, event-driven weather occurrences, such as hurricanes or floods, that can damage assets and disrupt operations. Chronic risks relate to longer-term climate shifts, such as rising temperatures or sea levels, affecting water supply, food security, infrastructure, and employee safety. Likewise, transition risks, including policy and legal, technological, market, and reputational risks, arise from the economic, regulatory, and technological adjustments necessary to mitigate climate change and transition to a low-carbon economy. Policy and legal risks arise from regulatory actions such as carbon pricing, mandates for energy efficiency, or litigation against firms for failing to mitigate or disclose climate-related risks. Technology risk arises from innovations such as renewable energy or battery storage that can disrupt existing systems, affecting cost structures and competitiveness. Market risk involves shifts in demand and supply driven by climate-related preferences or constraints. Reputational risk is closely tied to public and stakeholder perceptions regarding an organization's alignment with the transition to a sustainable economy. The extent and severity of these risks depend on the pace and scale of the transition, as well as the effectiveness of regulatory and corporate responses to mitigate them. As noted in the survey by Stroebel and Wurgler (2021), regulatory risks related to transitioning to a low-carbon economy are seen as the most significant climate threat in the short term. In contrast, physical risks from climate change are viewed as the most critical concern over the long term. According to NGFS (2021, 2024), climate change and the transition are likely to translate into financial risks, posing challenges to financial stability (Figure 2 and Figure 3).

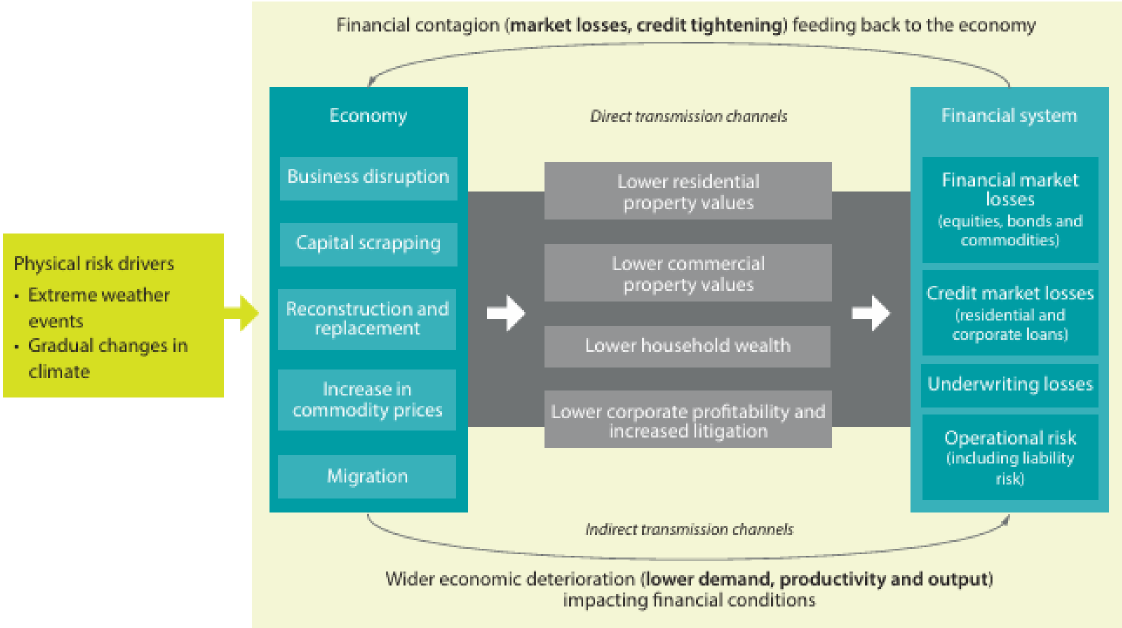

Figure 2. From physical risk to financial stability risks (NGFS, 2021)

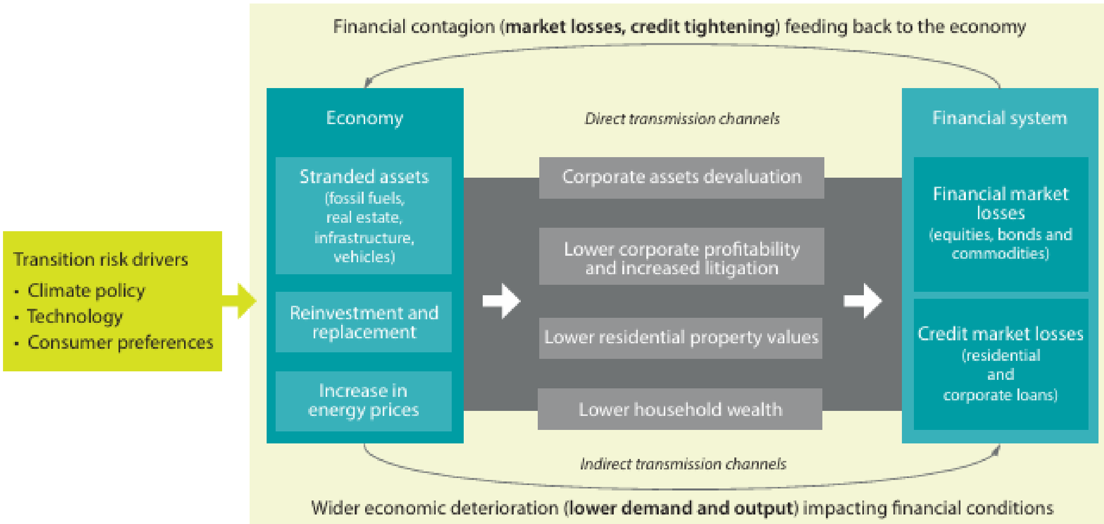

Figure 3. From transition risk to financial stability risks (NGFS, 2021)

The examination of climate risk implications for financial stability represents an emerging field of research, with critical knowledge gaps persisting in two main area: The quantitative evaluation of how both physical and transition climate risks propagate through macroeconomic systems and financial networks; The integration of climate-related information into financial asset valuation and portfolio risk management practice

(Battiston et al., 2021). Although climate risks are increasingly priced into markets, concerns remain that valuations do not fully reflect these risks. According to Eren et al. (2022), investors face three main challenges: limited hedging options due to the systemic nature of climate risks, high uncertainty around their impacts and policy responses, and incomplete or imperfect information on climate risks. Empirical evidence suggests that equity markets react to climate risks, but the efficiency and consistency of this pricing vary across firms, sectors, and geographies. Hong et al. (2019) find that drought risk, a physical risk driven by climate change, is inefficiently priced in stock markets, particularly in the food sector. Likewise, Bolton and Kacperczyk (2021) examine the impact of transition risks and present evidence that firms with higher carbon emissions exhibit significantly higher cost of capital, and that carbon intensity is negatively priced in stock returns. They identify a carbon premium, suggesting that investors demand compensation for holding carbon-intensive assets due to their exposure to climate-related risks. Furthermore, R. F. Engle et al. (2020) find that climate risks remain incompletely priced, especially over short time horizons. They develop a climate beta measure to capture a firm's sensitivity to climate news and show that firms with higher climate betas are more vulnerable to regulatory shifts and climate disasters. Their studies are among the first to empirically demonstrate that climate news has a significant impact on financial markets.

Investor preferences for sustainability also play a key role in equity markets. Pedersen et al. (2021) propose a theory in which ESG factors serve a dual purpose: they provide information about firm fundamentals and reflect investors' non-pecuniary preferences. The authors introduce the concept of the ESG-efficient frontier, an extension of traditional mean–variance portfolio theory that incorporates ESG scores. This framework illustrates how the highest Sharpe ratios can be achieved at different levels of ESG. The study categorizes investors into three types based on their ESG awareness. Equilibrium asset prices are determined by an ESG-adjusted capital asset pricing model. Their empirical findings also indicate that the highest Sharpe ratio is achieved at a relatively high ESG level, and that further increases in ESG alignment lead to only a slight decline in performance. This suggests that ethical investment objectives can be pursued at minimal cost. Similarly, Pástor et al. (2022) explore the impact of rising ESG preferences using the equilibrium asset pricing model. Stocks are priced by a two-factor asset pricing model, consisting of the market portfolio and the ESG factor, where green assets have positive ESG betas and brown assets have negative ESG betas. The authors find that investors with green preferences are willing to accept lower expected returns in exchange for environmental alignment. This behavior helps explain the premium for green stocks and the growing valuation gap between green and brown firms. Their model shows that ESG preferences influence not only expected returns but also capital flows and long-term firm valuation. Moreover, their extended model incorporates climate into investors' utility, allowing expected returns to depend not only on market betas and investors' preferences but also on climate betas, which measure firms' exposures to climate shocks. Evidence shows that brown assets have higher climate betas than green assets, making them riskier in terms of exposure to climate risks. As a result, brown assets must offer higher expected returns and tend to display positive CAPM alphas, not only due to investor aversion toward brown holdings but also because of their greater vulnerability to climate-related shocks.

3 LITERATURE REVIEW AND HYPOTHESES

The research builds upon two major studies: the stock market interdependence and connectedness, as well as the impact of climate risks on the stock market linkages.

3.1 Prior studies

3.1.1 Market interdependence and connectedness

Researchers have employed a range of econometric approaches to explore the complex structure of market linkages, from classical time-series models to more advanced nonlinear and regime-switching methods. Since the early investigation into market interdependence, empirical works have typically focused on return and volatility dynamics, rather than price levels, as key indicators of market linkages (King et al., 1994; Forbes & Rigobon, 2002; Bekaert et al., 2005). One of the most straightforward approaches involves using correlation analysis, where correlation coefficients are calculated between two asset returns to measure linear co-movement. While applicable for preliminary insights, this method assumes static relationships and is limited in capturing non-linear or time-varying dependencies, especially during market turbulence (Longin & Solnik, 2001; Ang & Chen, 2002). More sophisticated techniques are based on Vector Autoregression (VAR) and Vector Error Correction Models (VECM). VAR models, introduced by Sims (1980), enable the analysis of dynamic interactions among multiple time series without specifying prior causal relationships. This method examines how shocks to one market affect others over time through impulse response functions and forecast error variance decompositions. However, it assumes constant variance and thus fails to account for the volatility clustering typical of financial time series. To address this limitation, the Generalized Autoregressive Conditional Heteroskedasticity (GARCH) framework and its multivariate extensions (MGARCH) have been developed to model time-varying volatility and cross-market spillovers. Among these, the BEKK GARCH model (Kroner & Engle, 1995) ensures a positive definite covariance matrix and captures volatility transmission, though it can be computationally intensive in larger systems. The DCC-GARCH model (R. Engle, 2002) separates the estimation of variances and correlations, making it easier to model changing relationships over time. These multivariate GARCH models, synthesized and systematically reviewed in Bauwens et al. (2006), are handy for assessing how financial market co-movements evolve during periods of stress. Another approach that allows for the examination of how relationships between variables may vary, particularly in the tails of the distribution, is the quantile regression framework (Baur, 2013). It is crucial to understand various market movements and potential contagion effects among them. To fully quantify systemic risk contributions and capture nonlinear dependence structures under extreme conditions, researchers also apply extreme values in stress testing and risk management to estimate the likelihood of severe losses (Curcio et al., 2023). Additionally, copula models provide a flexible framework for modeling nonlinear and asymmetric dependencies, particularly effective in capturing tail dependence and joint extreme events that traditional correlation-based methods often fail to detect. However, these approaches do not quantify the exact magnitude of connectedness and cannot capture the dynamic evolution in the network over time.

Another important approach to capture intermarket connectedness and network linkages is the connectedness framework introduced by Diebold & Yilmaz (2009, 2012, 2014). Connectedness refers to how shocks to one market are transmitted to others, reflecting the underlying structure of interdependence within the financial system. The methodology is based on forecast error variance decompositions from the VAR model, which quantifies how much of the forecast error variance of one variable is attributable to shocks to other variables in the system. Unlike the other methods, this framework produces a set of intuitive spillover indices, including total, directional (to and from others), and net connectedness. They allow researchers to identify systemic risk contributors and receivers within a financial network. Since this time-domain connectedness does not distinguish between short- and long-term dynamics, Baruník & Křehlík (2018) extended it into the frequency domain, enabling the decomposition of connectedness into short-term, medium, and long-term spillovers. This enables researchers to analyze how shocks propagate over various investment horizons (M. Umar et al., 2022). Another notable approach is the quantile vector autoregression (QVAR) connectedness approach, as developed in recent work by Chatziantoniou et al. (2021) and Ando et al. (2022), which extends the connectedness framework into the quantile domain. QVAR allows the estimation of connectedness at different quantiles, specifically to capture tail-risk spillovers and asymmetric dependencies. Overall, each of these connectedness methodologies makes a unique contribution to understanding financial interdependence.

The interdependence of the stock markets in Europe and the Nordic regions has become more pronounced in recent decades as financial globalization has accelerated. Dengjun (2015) confirms that long- and short-run interdependence in Nordic stock markets has intensified, particularly in response to regional policy alignment and coordinated responses to financial crises. Using Johansen's cointegration technique and an exponential GARCH model, the study finds that market interdependence improved substantially up to 2008, with pronounced volatility spillovers between market pairs such as Sweden-Finland and Denmark-Norway. These findings suggest that financial cooperation enhances the synchronization of market dynamics, which can facilitate risk-sharing but also increase vulnerability to shocks. Recent studies have employed connectedness approaches to analyze the interdependence between markets, particularly during periods of market disruptions. Mensi et al. (2018) have shown that financial crises exacerbate volatility spillovers among global and regional markets, as well as within the GIPSI group. Using the Diebold & Yilmaz (2012, 2014) connectedness framework and an ADCC-GARCH model, the study documents how volatility transmission becomes more pronounced during crises such as the global financial crisis (GFC) and the Eurozone sovereign debt crisis (ESDC), highlighting financial contagion and the evolving topology of global market interdependence. Su (2020) uses a time-frequency decomposition approach to investigate volatility spillover behavior across G7 stock markets. The study finds that spillovers are highly sensitive to crises and exhibit distinct behaviors across short-, medium-, and long-term horizons. Low-frequency components are revealed to be the main contributors, while high-frequency components are sensitive to market shocks. Moreover, the study identifies key contributing factors that influence spillovers differently across various time horizons. Li (2020) investigates volatility spillovers across European stock markets amid Brexit uncertainty. Using a BEKK-GARCH model and variance decomposition based on the Diebold and Yilmaz framework, the study finds that while the UK was initially a dominant transmitter of volatility spillovers, its influence declined significantly following the Brexit referendum. France and Germany, on the other hand, increasingly became key transmitters of volatility within Europe. The study also finds that Brexit-related shocks remain substantial and may have long-lasting effects on market dynamics. Z. Umar et al. (2024) examine returns and volatility connectedness among Eurozone equity markets using a time-varying parameter vector autoregressive (TVP-VAR) model. Their findings confirm that Eurozone markets exhibit significant interconnectedness, with the most developed markets, such as France and Germany, acting as net transmitters of shocks. In contrast, smaller or newer Eurozone members, such as Lithuania, Slovenia, and Slovakia, were more vulnerable and emerged as net receivers of volatility. The findings suggest that countries with developed capital markets exert considerable influence over others. Similarly, Lang et al. (2024) employ the TVP-VAR method to analyze how extreme downside risks propagate across G7 stock markets during crisis periods, with a focus on the COVID-19 pandemic and its variants. The study identifies the UK and Italy as persistent transmitters of tail risk, while Japan consistently acts as a receiver. The analysis reveals that connectedness spikes during significant events, such as the pandemic outbreak, and then adjusts in response to government interventions, lockdown policies, and investor sentiment.

3.1.2 Climate risks and markets connectedness

The approaches to measure climate risks have evolved significantly over time, reflecting both advances in data availability and growing recognition of climate-related financial vulnerabilities. To model climate risks, researchers must identify key sources of uncertainty relevant to the processes of climate change and the economy, such as uncertainty about future economic growth, climate developments, and model parameters, as each type of uncertainty influences asset prices and risk premia differently (Giglio et al., 2020). Since climate risks are difficult to observe directly, researchers have relied on various proxy variables, including temperature anomalies, emissions data, carbon market data, climate news indices, and investor sentiment measures, to model and analyze their financial implications (Venturini, 2022). Among environmental data proxies, global temperature anomalies are used to capture long-term global warming trends as a risk factor. The GISTEMP dataset[1], provided by the NASA Goddard Institute for Space Studies (GISS), reports monthly global surface temperature anomalies, which measure the degree to which each month's average global temperature deviates from a historical baseline. This dataset is a common proxy for the long-term global warming trend (Cao, 2025). Another source is the EM-DAT international disaster database[2], which records occurrences of natural disasters worldwide. Researchers can extract the number of climate-related disasters per year or associated damage estimates as proxies for physical climate risks (Jin et al., 2023). In addition, carbon emissions or greenhouse gas levels served as forward-looking indicators of both physical and transition risk, under the claim that higher emissions increase future physical risk and likely lead to more aggressive policy responses (Ilhan et al., 2021). Other publicly available databases, such as those provided by the World Bank and OECD, publish CO_2 emissions by country. Furthermore, the carbon price is increasingly used as a market-based indicator of transition risk sentiment, reflecting expectations about regulatory stringency and market decarbonization.

In recent years, the development of text-based indices has opened new avenues for measuring climate risk by capturing investor attention, policy discourse, and media sentiment. These indices utilize natural language processing (NLP) to extract climate-related signals from large volumes of unstructured text, offering high-frequency and sentiment-sensitive proxies suitable for financial market analysis. One of the earliest and most influential contributions is the Climate News Index, developed by Engle et al. (2020), which quantifies the volume and tone of climate-related media coverage by analyzing articles from major newspapers. Similarly, Faccini et al. (2023) and Bua et al. (2024) developed

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[1] Data.GISS: GISS Surface Temperature Analysis (GISTEMP v4)

[2] EM-DAT - The international disaster database

climate risk proxies relating to physical risks and transition risks by scanning news for climate-related content. These indices are constructed daily, making them particularly valuable for studies on the high-frequency financial market. Likewise, Q. Li et al. (2024) introduced firm-level climate risk exposure measures using textual analysis based on the earnings call transcripts regarding physical and transition risks. Another index is the Climate Policy Uncertainty (CPU) Index by Gavriilidis (2021), which follows the methodology used in building the Economic Policy Uncertainty (EPU) Index by Baker et al. (2016). This index tracks the degree of uncertainty in climate-related policy by measuring the co-occurrence of key terms. Similarly, Ardia et al. (2023) construct a Media Climate Change Concerns Index (MCCC)[3] using text analysis of major newspapers.

More recent studies have assessed how climate risks shape broader financial interconnectedness. Using a nonlinear network model and the Global Climate Change News Index, Mao et al. (2023) analyzes how climate risk propagates through global asset classes, including stocks, bonds, commodities, and currencies. The study finds that stock and bond markets are key transmitters of climate risk, while commodities and currencies are more reactive. Notably, climate shocks had a more substantial systemic influence before 2008, possibly due to less market adaptation or weaker climate disclosures at the time. Zhao et al. (2023) investigates the interconnectedness between oil prices, carbon emission prices, and stock markets, using frequency-domain spillover models. The study reveals that, although total spillover is relatively low, short-term spillovers from carbon markets intensify during crises, thereby reinforcing risk as a dynamic contributor to financial contagion.

Furthermore, a growing body of literature also examines how climate risk impacts stock market interdependence across different geographies and regimes. Z. Umar et al. (2020) analyze the static and dynamic connectedness of ESG investments across ten developed and emerging markets. Their results show significant and persistent risk transmissions among ESG markets, especially during episodes of financial stress such as the European

[3] MCCC | Sentometrics Research

debt crisis, the Greek bailout, and the COVID-19 outbreak. The study finds that the United States, Canada, Europe, and the UK are key net transmitters of shocks, while Japan, China, and India are consistently net receivers. Furthermore, the VIX volatility index plays a central role in transmitting shocks across ESG markets, reinforcing the view that uncertainty-driven contagion is a key transmitter. These findings suggest that the benefits of diversification from ESG investments diminish significantly during periods of heightened global risk. Extending this analysis, Gao et al. (2022) use both time-domain and frequency-domain spillover indices to study ESG risk transmission across eight major regional markets. Their findings confirm strong global ESG interconnectedness, with developed markets, such as North America and Europe, serving as central risk transmitters, while emerging markets in the Asia-Pacific, the Middle East, and Africa act as net receivers. The study further reveals that medium-frequency spillovers are the strongest, although high- and low-frequency spillovers rise sharply during crises, such as COVID-19. These insights highlight that ESG markets not only reflect climate-related risk pricing but also act as amplifiers of systemic contagion under volatile conditions. Similarly, Guo et al. (2024) employ the TVP-VAR framework and construct a two-layer network across six advanced economies to investigate how climate transition risks influence cross-country risk spillovers. It finds that France and Germany are consistent net risk transmitters, while Japan and Canada are net receivers. Besides, spillovers are found to intensify during crisis periods. Wan et al. (2024) utilizes a time-frequency perspective to eleven global ESG stock indices across developed and developing markets. Their findings show European ESG markets are more influential in transmitting shocks, whereas Asian indices are more vulnerable or net receivers. Short-term connectedness dominates during crisis periods, while long-term spillovers are present but weaker, indicating that ESG markets are susceptible to short-lived contagion effects. Recently, Hoque et al. (2024) investigates the interconnectedness among seven MSCI climate change stock indices across different quantiles and how this connectedness is affected by uncertainty indicators. The results show strong connectedness across regimes, with short-term spillovers prevailing over long-term spillovers in all regimes. The USA and North America are consistent net transmitters of spillovers, while Japan, EM, and Asia-Pacific are consistent net receivers.

Events such as the Paris Agreement (2015), the US withdrawal (2016), the COVID-19 pandemic (2020), and the Russia-Ukraine War (2022) significantly increased connectedness. Cao (2025) explores tail-risk connectedness across social sectors in the US, Europe, and China, using ARMA-GJR-GARCH and TVP-VAR frameworks. The results indicate that physical climate risks amplify systemic tail dependencies, while transition risks generally mitigate these extreme linkages.

These empirical findings collectively demonstrate that climate risks, particularly in their various forms of physical and transition threats, have become an important structural force shaping the connectedness of financial markets. The impacts of climate risks may vary across regions and time horizons, with developed markets often serving as net transmitters and emerging markets as net receivers. Given that Nordic markets are highly integrated with global financial systems and increasingly exposed to climate-sensitive matters, climate risk may substantially alter return correlations, especially during periods of financial distress. This highlights the importance of examining stock market interdependence in the Nordic region in light of climate risk perceptions.

3.2 Hypotheses development

This study examines the return interdependence among Nordic stock markets, with a specific focus on the role of climate risk as a potential driver of market connectedness. It contributes to the growing body of literature on stock market connectedness and systemic risk, particularly by examining how both physical and transition climate risks influence the dynamics of cross-market interactions. In addition, the study explores whether the degree of connectedness differs across the distribution of returns, specifically in the upper and lower quantiles. This allows for covering asymmetric spillover effects, highlighting how interdependence behaves under extreme market conditions. Specifically, we propose the following hypotheses:

Hypothesis 1: There is significant return connectedness among the Nordic stock markets and other major stock markets.

Hypothesis 2: The strength of connectedness among stock markets varies across different market regimes (normal vs. extreme conditions), with greater spillovers during extreme conditions.

Hypothesis 3: Physical climate risks increase the return connectedness among stock markets.

Hypothesis 4: Transition climate risks increase the return connectedness among stock markets.

4 DATA AND METHODOLOGY

4.1 Data

To examine the interdependence among Nordic stock markets, this study utilizes four major stock indices: the OMX Helsinki 25 (OMXH25), OMX Stockholm 30 (OMXS30), OMX Copenhagen 20 (OMXC20), and OBX (OBXO20), representing the stock markets' return for Finland, Sweden, Denmark, and Norway, respectively. Acknowledging that global financial dynamics certainly influence fluctuations in these markets, the study includes four additional major stock indices: the S&P 500, STOXX Europe 600, NIKKEI 225, and SHANGHAI Composite, which represent the U.S., European, Japanese, and Chinese stock markets, respectively. This broader selection enables an examination of how major global markets contribute to the overall connectedness within the network. Daily data for all eight indices are collected from January 1, 2000, to December 31, 2024. This period covers several significant events, including the Global Financial Crisis (GFC), the Covid-19 pandemic, and the ongoing Russia-Ukraine conflict. These indices are retrieved from the LSEG Workspace. To compute the daily return series for each market, we take the natural logarithm of the ratio of consecutive daily closing prices.

$$R_{it} = \ln(P_{it} - P_{it-1}) \times 100 \tag{1}$$

Where y (R_{it}) denotes the daily return of market i at time t, P_{it} and P_{it-1} are the closing prices on day t and t-1, respectively.

Furthermore, to determine the impact of climate risks on the interdependence of Nordic stock markets, this study employs the climate Physical Risk Index (PRI) and the Transition Risk Index (TRI), as developed by Bua et al. (2024). These indices[4] are constructed using a text-based approach grounded in a comprehensive set of authoritative climate-related

[4] https://www.policyuncertainty.com/Climate_Risk_Indexes.html

sources. The climate risk data are available from 01 January 2005 to 31 December 2023. The underlying idea is to retrieve daily innovations in climate risk perception by processing news media content over time. Specifically, the authors first develop two distinct vocabularies representing physical and transition climate risks. These vocabularies are collected from many scientific and governmental texts related to climate change, starting with the database used by R. F. Engle et al. (2020). The content is carefully reviewed, and only texts related to physical or transition risk are retained. In addition, financial texts that discuss both types of climate risks are included to ensure that the resulting risk measures reflect multiple perspectives. Next, to quantify how much each news document discusses climate risks, they calculate the cosine similarity between the daily news vectors and the physical (PRI) and transition (TRI) vocabulary vectors. Cosine similarity is a widely used text-analysis technique that measures the angular distance between two text vectors: the closer the vectors point in the same direction, the higher the similarity score, indicating stronger alignment between the news content and the respective climate risk category. These cosine similarity scores form two separate “concern” time series, which capture the daily intensity of news coverage related to physical and transition climate risks. The final PRI and TRI indices are then constructed as the residuals from autoregressive (AR(1)) models of the concern series. In this way, PRI and TRI represent daily shocks or innovations in the discourse around climate risk. Spikes in the indices correspond to unexpected increases in media attention to physical and transition risks.

In addition to climate risks variables, following prior studies (Basher & Sadorsky, 2024; Hoque et al., 2024; Cao, 2025), three key control variables are included in the model to account for other influential factors affecting the Total Connectedness Index (TCI) among markets: investor sentiment, economic policy uncertainty, and geopolitical risk index. To proxy investor sentiment and risk aversion within these markets, the EURO STOXX 50 Volatility index (VSTOXX) is incorporated. Similar to the CBOE Volatility Index (VIX) in the U.S., the VSTOXX is often referred to as the ”fear index” of Eurozone markets. It measures the implied volatility of near-term option prices on the EURO STOXX 50 index, comprising 50 of the largest and most liquid stocks in the Euro area. A high VSTOXX implies increased uncertainty or risk aversion among investors. Daily VSTOXX data is collected to assess how fluctuations in regional market sentiment influence the degree of connectedness among the stock markets. Besides, to account for economic policy uncertainty in the region, the daily UK Economic Policy Uncertainty (EPU) Index is used as a proxy for economic policy uncertainty within the broader European region. While the index is country-specific, the UK's strong financial and trade linkages with other European countries make it a relevant indicator of regional uncertainty. Therefore, the inclusion of this variable helps assess how uncertainty related to policy developments affects market interdependence in the European context. Furthermore, the Geopolitical Risk (GPR) Index[5] is incorporated to capture the influence of geopolitical tensions and conflicts on market dynamics. The GPR index is constructed through an automated text-search methodology that systematically scans the electronic archives of ten newspapers, quantifying the articles reporting adverse geopolitical events. These events consist of a broad spectrum of occurrences, including political instability, military conflicts, terrorism, and diplomatic disputes. Increased geopolitical tensions are correlated with a higher likelihood of economic disasters and larger downside risks to the global economy.

Accordingly, the empirical analysis is divided into two phases: (1) an initial analysis using the full 2000-2024 dataset to measure stock market interdependence, offering a perspective on return spillovers and network dynamics among markets; and (2) an analysis on the 2005-2023 period, during which detailed climate risk data is available, assessing the specific effects of physical and transition climate risks on markets connectedness - while controlling for investor sentiment and economic policy uncertainty.

[5] https://www.matteoiacoviello.com/gpr.htm

4.2 Research method

4.2.1 Quantile vector autoregression approach

Since one of the main objectives of this study is to examine the quantile connectedness of Nordic stock markets, return spillovers are measured at the median, extreme low, and extreme high quantiles. Similar to prior studies (Lorente et al., 2023; Hoque et al., 2024; Cao, 2025), this study employs the Quantile Vector Autoregression (QVAR) connectedness approach, as developed in recent work by Chatziantoniou et al. (2021) and Ando et al. (2022). This methodology extends the connectedness framework introduced by (Diebold & Yilmaz, 2009, 2012, 2014) into the quantile domain, allowing for the assessment of interdependence across financial markets on average and under different market conditions, such as bearish, normal, and bullish states, denoted by specific quantiles ($\tau \in [0, 1]$). QVAR(1), with a lag length of 1, can be outlined as in the following equation:

$$y_t(\tau) = \mu(\tau) + \phi_1(\tau) y_{t-1} + u_t(\tau) \tag{2}$$

Where y_t is k x 1 dimensional endogenous variable vector of returns, $\mu(\tau)$ is a k x 1 dimensional conditional mean vector, $\phi_1(\tau)$ is a k x k dimensional variance-covariance matrix, $u_t(\tau)$ is the error process. τ is between [0, 1] and represents the quantile of returns, t indexes the time from 1 to T. Then, Wold's theorem is used to transform equation (2) into a quantile vector moving average representation, QVMA(∞). In equation (3), y_t is rewritten in terms of the moving average process of an infinite-order vector, and y_t is defined by the sum of the residuals. In other words, $\mu(\tau)$ represents the fixed, baseline level that y_t at quantile τ would maintain if no shock. $A_i(\tau)$ is the matrix that captures how each lag of shocks $u_{t-i}(\tau)$ affects y_t over time.

$$y_t(\tau) = \mu(\tau) + \sum_{i=0}^{\infty} A_i(\tau)\, u_{t-i}(\tau) \tag{3}$$

In addition, the Generalized Forecast Error Variance Decomposition (GFEVD) approaches, developed by (Koop et al., 1996; Pesaran & Shin, 1998), is calculated to assess the impact of a shock in variable j has on the forecast error variance of variable i for the forecast horizon H, quantile (τ):

$$\theta_{ij,\tau}^{g}(H) = \frac{\sigma_{jj}^{-1} \sum_{h=0}^{H-1} \left(e_i' A_h(\tau) \sum(\tau) e_j\right)^2}{\sum_{h=0}^{H-1} (e_i' A_h(\tau) \sum(\tau) A'_h(\tau) e_i)} \tag{4}$$

In the equation (4) above, $\theta_{ij,\tau}^{g}(H)$ represents the contribution of the j variable to the variance of forecast error of the variable i on the horizon H at quantile (τ), $\sum(\tau)$ illustrates the covariance matrix of the vector of errors, σ_{jj} denotes the jth diagonal element of the residual covariance matrix $\sum(\tau)$. $A_h(\tau)$ is the moving average coefficient matrix at lag h for quantile (τ), and e_i is a vector of value 1 for the ith element and 0 elsewhere. Moreover, to ensure the entries in each row of the GFEVD matrix sum to 1, we normalize every entry of the variance decomposition matrix using the equation (5). This normalization provides a proportional interpretation, making the total contribution of shocks from all variables to the forecast error variance of variable i equal to 100%. $\theta_{ij,\tau}^{\sim g}(H)$ is the percentage of forecast error variance in variable i explained by variable j.

$$\theta_{ij,\tau}^{\sim g}(H) = \frac{\theta_{ij,\tau}^{g}(H)}{\sum_{j=1}^{k} \theta_{ij,\tau}^{g}(H)} \tag{5}$$

Finally, different dynamic indices are computed to evaluate not only the contribution of each market to risk spillovers but also the overall connectedness within the network. Among these, the Total Connectedness Index (TCI) at quantile τ is the sum of off-diagonal elements in the normalized GFEVD matrix, representing the total spillovers across variables in the system. A high TCI corresponds to a great degree of connectedness in the system. Specifically, $TCI_\tau(H)$ is computed as follows:

$$TCI_\tau(H) = \frac{\sum_{i,j=1,i\neq j}^{m} \theta_{ij,\tau}^{\sim g}(H)}{m} \times 100 \tag{6}$$

Additionally, for quantiles τ, the directional connectedness from all other variables j to variable i ("FROM" / Receiver from others) is given as follows:

$$FROM_{\mathrm{i},\tau}(\mathrm{H}) = \sum_{j=1, i \neq j}^{m} \theta_{\mathrm{ij},\tau}^{\sim g}(\mathrm{H})\ x\ 100 \quad (7)$$

In contrast, the directional connectedness from variable i to all other variables ("TO" / Transmitter to others) on quantile τ can be expressed as follows:

$$TO_{i,\tau}(\mathrm{H}) = \sum_{j=1, i \neq j}^{m} \theta_{\mathrm{ji},\tau}^{\sim g}(\mathrm{H})\ x\ 100 \quad (8)$$

The difference between the total directional connectedness to others and the total directional connectedness from others gives us the net total directional connectedness ("NET") for the quantiles τ:

$$NET_{i,\tau}(\mathrm{H}) = TO_{i,\tau}(\mathrm{H}) - FROM_{\mathrm{i},\tau}(\mathrm{H}) \quad (9)$$

To get the TCI at different quantiles, a rolling window of 200 days or 100 days is applied, and the GFEVD horizon of 10 is selected. The study's computations are carried out using Excel and RStudio.

4.2.2 Determinant of dynamic connectedness

The study further investigates the determinants of return connectedness among stock markets by examining the impacts of climate risks and other uncertainty factors. This approach builds upon a growing body of literature that positions climate-related risks as primary explanatory variables when modelling their impacts on the level of financial markets' interdependence (Basher & Sadorsky, 2024; Cao, 2025). Existing studies have shown that physical climate events, such as extreme weather hazards, tend to intensify volatility and return spillovers, particularly across climate-sensitive sectors like energy, financials, and utilities. Meanwhile, transition risks likely affect carbon-intensive ("brown") sectors, while potentially benefiting environmentally sustainable ("green") sectors. Several studies also explore the extent to which such risks are priced in financial markets. Moreover, recent advancements in measuring climate risk perception extend beyond traditional indicators such as temperature and CO_2 emissions to include forward-looking and sentiment-based proxies, such as media climate change concern indices, Google Search Volume Index (GSVI) related to climate change, and other text-based measures derived from news sources. These proxies assess shifts in investor attention, particularly during periods of environmental policy uncertainty or intense climate news.

In line with this strand of literature, we incorporate two categories of climate risk variables - physical risks (PRI) and transition risks (TRI) – as main regressors in our empirical analysis. These daily indicators, derived from the work of Bua et al. (2024), are designed to examine whether two dimensions of perceived climate risks have statistically significant impacts on market linkages. PRI covers narratives related to acute and chronic physical climate events, while the TRI reflects uncertainty surrounding the transition toward a low-carbon economy. By integrating these measures, we aim to assess how each dimension of climate risks contributes to the dynamics of network connectedness among Nordic and other equity markets. This approach offers a more granular understanding of climate risk transmission channels in regional and global equity markets.

The dependent variable in this study is the Total Connectedness Index (TCI), computed using the quantile connectedness framework. Within the QVAR framework, we obtain time-varying indicators of TO, FROM, and NET spillovers for each market, as well as the TCI, which serves as a measure of overall connectedness across the network. To evaluate the influence of climate risks on network connectedness, the TCI series (generated via rolling window estimations) is used as the dependent variable in the regression model. In addition to climate-related variables, we account for other potential sources of uncertainty that may influence market connectedness. Although uncertainty plays a prominent role in shaping economic and financial decisions, it is inherently unobservable and challenging to measure directly. To address this, we utilize a set of widely accepted proxy variables that capture distinct dimensions of uncertainty. Specifically, the VSTOXX index is included as a proxy for market sentiment. The Economic Policy Uncertainty (EPU) index and the Geopolitical Risk (GPR) index are used to quantify uncertainty related to economic policy and geopolitical events, respectively. These three variables - investor sentiment, economic policy uncertainty - are widely recognized in the literature as influential drivers of asset pricing, volatility, and return spillovers, particularly during periods of market stress (Urom & Ndubuisi, 2023; Hoque et al., 2024; Basher & Sadorsky, 2024; Cao, 2025).

The following time-series regression model is estimated using the Ordinary Least Squares (OLS) method:

$$TCI_t = \beta_0 + \beta_1 PRI_t + \beta_2 \, TRI_t + Control_t + \varepsilon_t \tag{10}$$

Where: TCI_t is the Total Connectedness Index among stock markets at time t; PRI_t and TRI_t are daily climate risk indicators; $Control_t$ represents control variables, and ε_t is the error term.

5 EMPIRICAL RESULTS

The empirical results begin with an overview of the dataset, comprising eight stock markets, along with key descriptive statistics for these indices. The analysis then investigates return connectedness among the Nordic and global stock markets using both static and dynamic approaches. While the static connectedness analysis provides insights into the average spillover effects across markets, the dynamic analysis shows the evolution of return interdependencies over time. Using the total connectedness index derived in this phase, the study proceeds to examine the role of climate risks in shaping market interdependence. This includes presenting additional data and empirical findings that assess how both physical and transition climate risks influence the linkage between markets.

5.1 Data description

Table 1 reports the descriptive statistics for the daily return series of eight stock markets from 2000 to 2024. The four Nordic countries include Finland (OMXH25), Sweden (OMXS30), Denmark (OMXC20), and Norway (OBXO20). Four other major global stock markets are the U.S. (S&P 500), Europe (STOXX 600), Japan (NIKKEI 225), and China (SHANGHAI). The number of observations for each market is 6,219. The mean daily return of each index is approximately zero, implying the short-term nature of daily data. In terms of volatility, measured by the standard deviation, the Chinese market (SHANGHAI) has the highest level of daily stock fluctuations among the sample, indicating relatively greater market volatility. Regarding extreme values, the Copenhagen market (OMXC20) recorded the most significant daily loss at -14.2% while the Chinese market (SHANGHAI) experienced the smallest minimum daily return, at -9.3%, reflecting varying degrees of downside tail risk across markets. Likewise, maximum daily gains range from 9% to 13%, with the Japanese market (NIKKEI 225) showing the highest single-day return. All indices show negative skewness (left skew), indicating a higher probability of extreme negative returns than positive ones. This asymmetry emphasizes the prevalence of downside risk in global and regional equity markets. Moreover, the kurtosis values of all return series are significantly greater than 3, confirming the presence of leptokurtosis, characterized by fat tails and sharp peaks. S&P 500 has the highest kurtosis, suggesting a relatively higher frequency of extreme values compared to other markets.

Table 1. Descriptive statistics for stock indices

	Obs	Mean	Std.dev	Min	Max	Skew	Kurtosis	JB test	ADF test
OMXH25	6219	0.0000	0.014	-0.107	0.093	-0.231	7.375	5016***	-18.97**
OMXS30	6219	0.0001	0.014	-0.112	0.099	-0.090	7.496	5245***	-19.49**
OMXC20	6219	0.0003	0.013	-0.142	0.095	-0.423	9.932	12635***	-17.89**
OBXO20	6219	0.0003	0.014	-0.113	0.110	-0.603	10.344	14352***	-18.04**
S&P 500	6219	0.0002	0.012	-0.128	0.110	-0.464	12.990	26082***	-18.04**
STOXX 600	6219	0.0000	0.012	-0.122	0.094	-0.373	10.304	13968***	-19.06**
NIKKEI	6219	0.0001	0.014	-0.132	0.132	-0.436	10.599	15161***	-18.42**
SHANGHAI	6219	0.0001	0.015	-0.093	0.094	-0.297	9.071	9643***	-17.2**

Note: ***,** indicates the null hypothesis is rejected at the 1%, 5% significance level

Jarque-Bera (JB) Test: The JB test is employed to assess the normality of the return distribution. The null hypothesis (H0) is that the data follows a normal distribution. Across all market indices, the test statistics significantly reject the null hypothesis. In conjunction with the observed non-zero skewness and high kurtosis values, these results provide strong evidence against the assumption of normal distributions. The return series exhibits non-normal and fat-tailed distributions.

Augmented Dickey-Fuller (ADF) Test: The ADF test examines the stationarity of the time series. The null hypothesis (H0) assumes that the time series has a unit root and is non-stationary. The ADF test results reject the null hypothesis for all indices under study, suggesting that the return series are stationary. Direct modeling can be applied without additional transformation.

Furthermore, Figure 4 plots the return series (blue line) and price levels (red line) of all eight stock markets over twenty-five years. Across all panels, the return series are centered around zero, confirming the earlier statistical findings that the mean returns are approximately zero over the long term. The return plots appear to display volatility clustering, where periods of high volatility are followed by periods of high volatility and vice versa. Volatility spikes are observed during disruptive events, including the Global Financial Crisis (2008-2009) and the COVID-19 pandemic (2020), as well as other region-specific events.

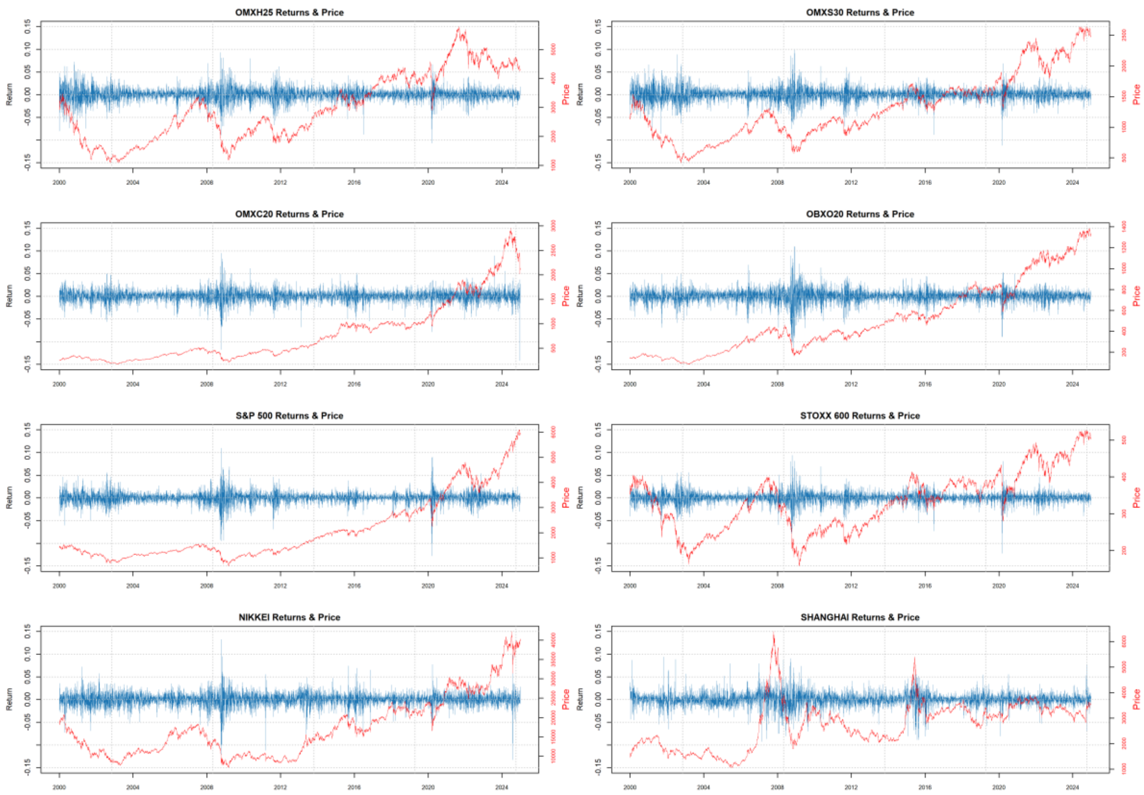

Figure 4. Plots of daily returns and prices for stock markets from 2000 to 2024

The price shows long-term upward trends, although punctuated by temporary yet sharp corrections during crisis periods. Among the four Nordic stock markets, the Finnish (OMXH25) and Swedish (OMXS30) indices show remarkably similar patterns: a dramatic decline during the early 2000s, followed by a recovery and a peak just prior to the 2008 financial crisis. After hitting their troughs around 2009, both indices resumed steady upward momentum, with only minor interruptions. During the COVID-19 shock in 2020, both markets experienced a sharp but brief decline, after which their upward growth continued. However, over the past three years, while the Finnish stock market has declined, returning to levels last observed before the COVID-19 pandemic, the Swedish market has continued to rise and reached a historical peak. Besides, the Danish (OMXC20) and Norwegian (OBXO20) indices display a more consistent long-term upward trend, with relatively abrupt downturns during global crises.

Figure 5 displays the Quantile-Quantile (Q-Q) plots for the daily return series of eight stock indices over twenty-five years. Q-Q plots are particularly useful for assessing whether a dataset is normally distributed. In each panel, the blue line represents the quantiles of the sample data, while the red diagonal line represents the expected quantiles under a normal distribution. A perfect fit to normality would result in the blue line closely following the red reference line across all quantiles. However, consistent across all indices, the blue lines deviate substantially from the red line in the tails, indicating that the actual return distributions exhibit heavier tails than the normal distribution. This deviation confirms the presence of leptokurtosis (fat tails), which was also supported by the earlier Jarque-Bera test results and descriptive statistics. Moreover, some indices display slight asymmetry in the Q-Q plots, where the lower and upper tails deviate unequally. This suggests the presence of negative skewness (left-tail risk), consistent with the observed skewness statistics in the summary table.

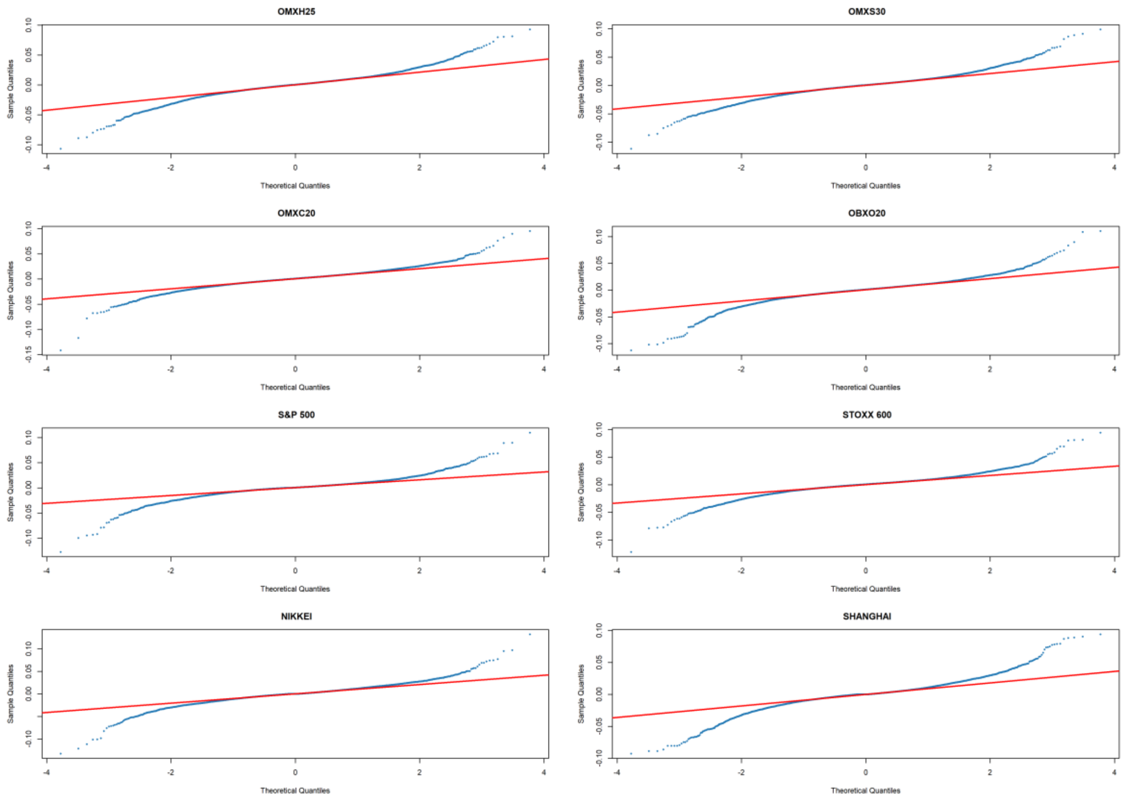

Figure 5. Q-Q Plots of daily returns for stock markets from 2000 to 2024

Figure 6 demonstrates the correlation matrix of the daily returns across stock indices. The upper triangle displays the Pearson correlation coefficients, while the lower triangle provides the corresponding scatterplots with fitted regression lines. Diagonal plots show the distribution of returns for each index. The statistical significance of correlations is denoted by asterisks, with all correlation coefficients being positive and significant at the 1% level. The results show strong correlations among European countries, reflecting a high degree of regional integration. In particular, the correlation between OMXH25 (Finland) and OMXS30 (Sweden) is 0.83, indicating a strong and statistically significant co-movement. Other pairs of Nordic markets also exhibit high correlations, all exceeding 0.6. Besides, Nordic countries demonstrate strong positive correlations with the broader European benchmark, reinforcing their integration with other European equity markets. In the meantime, correlations between Nordic indices and the U.S. market (S&P 500) are lower, suggesting moderate linkages. In contrast, correlations involving Asian markets, particularly with China, are weak. The histograms along the diagonal indicate that most return distributions are approximately symmetric but exhibit leptokurtosis, indicating the presence of fat tails.

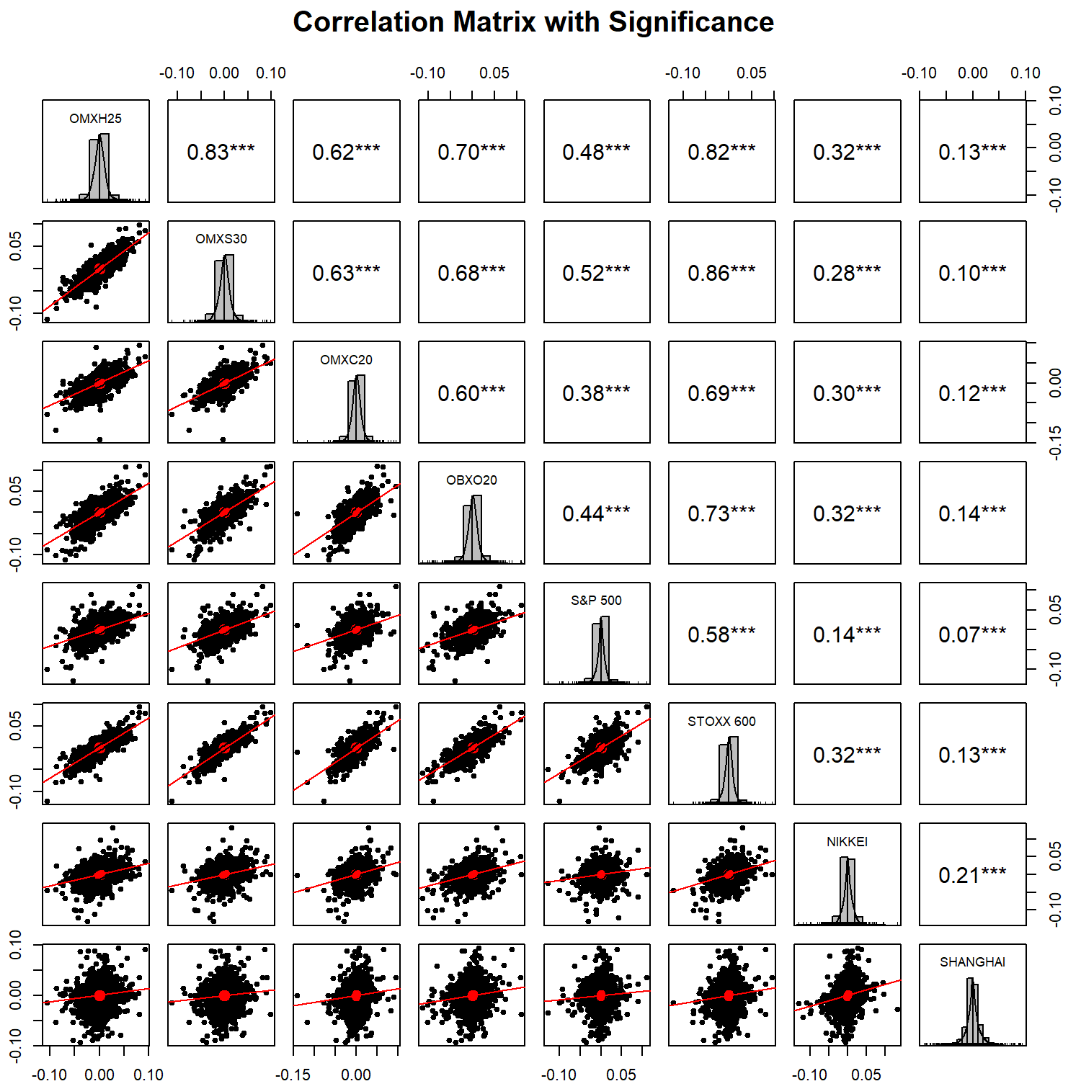

Figure 6. Correlation coefficient matrix of daily returns for stock markets

Note: *p<0.1; **p<0.05; ***p<0.01

5.2 Return connectedness among stock markets

5.2.1 Static connectedness analysis

Table 2 presents the return connectedness among eight markets at three different quantiles over the whole sample period. Each ij-element, corresponding to the ith row and jth column, reports the pairwise directional connectedness from market j to market i, measuring the extent to which shocks originating in market j contribute to the forecast error variance of market i. The ”FROM” column summarizes the total influence received by each market from all other markets, calculated as the sum of the off-diagonal elements in each row. Conversely, the ”TO” row represents the total spillovers transmitted by one market to all other markets, derived from the sum of off-diagonal elements in each column. The "NET" row is computed as the difference between "TO" and "FROM" values, indicating whether a market is a net transmitter (positive value) or net receiver (negative value) within the system. The Total Connectedness Index (TCI), calculated as the average of all off-diagonal spillovers, reflects the overall degree of return connectedness and serves as a measure of market interdependence.

Panel A shows the static return connectedness at the median quantile ($\tau = 0.5$) for average market conditions. The TCI value is 59.79, indicating that nearly 60% of the average forecast error variance in the system is due to cross-market spillovers instead of each market’s shocks. This reflects a pretty high level of systemic market interdependence among these equity markets. Nordic stock markets show strong bilateral connectedness, particularly between Sweden and Finland, with directional connectedness values of 18.77 and 18.46, respectively. Moreover, the Nordic region is also significantly influenced by broader European markets, with high directional values from the STOXX 600 to Finland (18.64), Sweden (19.85), Denmark (16.17), and Norway (16.47). These findings prove that Nordic markets' exposure to shocks originates from the wider European equity landscape. The NET row shows the dominant role of developed markets in transmitting shocks, with the highest values for STOXX 600 (26.35), followed by OMXS30 (15.72). In contrast, Asian markets act predominantly as shock absorbers, with NIKKEI exhibiting the largest negative net connectedness (-43.49), and SHANGHAI also functioning as a net receiver (-6.5). While the S&P 500 still shows positive net spillover within the system, its directional spillovers to other markets are modest. Its impact on the Nordic region is less pronounced than that of the European markets. Overall, while Sweden and Finland are found to be the net transmitters, Denmark is identified as a net receiver, and Norway appears to be relatively neutral, with a near-zero net connectedness.

Panels B and C present the static return connectedness at the lower and upper quantiles, respectively, examining the system behavior during extreme negative and positive return conditions. These results enhance understandings of market dynamics during troughs and peaks. The TCI values at these two quantiles are 83.67 (downside) and 82.77 (upside), both of which are substantially higher than under normal conditions. These values indicate intensified systemic linkages during both downturns and rallies, showing that co-movements increase in both bear and bull markets. The FROM values across most markets exceed 80, suggesting that each market is highly exposed to shocks from the rest of the system. Broad European markets, as well as Sweden and Finland, consistently emerge as transmitters in both regimes. These markets, along with the U.S., play dominant roles as transmitters of return shocks during market downturns. However, during favorable market conditions, the U.S. shifts slightly to a receiver, suggesting that it may not actively propagate its returns to other markets in favorable conditions. Meanwhile, Japan and China remain net receivers in both tails, but their FROM and TO values increase steadily, indicating greater integration into the global system under extreme conditions. The Chinese market, in particular, appears more vulnerable due to its rising directional values under both tails. The Nordic region continues to display strong interlinkages in both negative and positive market regimes, with Sweden and Finland consistently acting as net contributors to the system. At the same time, Denmark and Norway are more passive or balanced.

Table 2. Static connectedness analysis

Panel A. Return connectedness at the median (τ = 0.5)

τ = 0.5	**OMX H25**	**OMX S30**	**OMX C20**	**OBX O20**	**S&P 500**	**STOXX 600**	**NIKKEI**	**SHANG HAI**	**FROM**
OMXH25	28.03	18.77	9.82	12.83	9.62	18.64	1.93	0.36	71.97
OMXS30	18.46	27.65	10.11	11.89	9.91	19.85	1.88	0.25	72.35
OMXC20	12.57	13.14	35.51	11.52	8.71	16.17	2.07	0.32	64.49
OBXO20	14.89	14.04	10.52	32.55	8.54	16.47	2.48	0.52	67.45
S&P 500	11.51	13.00	7.35	9.22	40.52	16.17	1.95	0.28	59.48
STOXX 600	17.02	18.53	11.57	12.98	11.45	25.79	2.32	0.34	74.21
NIKKEI	9.13	9.62	6.32	8.16	12.40	11.82	41.40	1.16	58.60
SHANGHAI	1.27	0.97	1.01	1.54	1.00	1.45	2.49	90.26	9.74
TO	84.86	88.07	56.70	68.13	61.63	100.56	15.11	3.23	478.29
Inc.Own	112.89	115.72	92.21	100.68	102.15	126.35	56.51	93.50	
NET	12.89	15.72	-7.79	0.68	2.15	26.35	-43.49	-6.50	**59.79**

Panel B. Return connectedness at the lower tail (τ = 0.05)

τ = 0.05	**OMX H25**	**OMX S30**	**OMX C20**	**OBX O20**	**S&P 500**	**STOXX 600**	**NIKKEI**	**SHANG HAI**	**FROM**
OMXH25	15.48	14.08	12.24	12.83	12.45	14.13	9.97	8.81	84.52
OMXS30	14.01	15.46	12.31	12.62	12.57	14.32	10.00	8.70	84.54
OMXC20	12.95	13.15	16.23	12.64	12.09	13.67	10.25	9.01	83.77
OBXO20	13.35	13.32	12.41	15.94	12.19	13.74	10.17	8.89	84.06
S&P 500	12.78	13.13	11.87	12.14	16.97	13.65	10.26	9.20	83.03
STOXX 600	13.70	14.06	12.55	12.80	12.88	15.24	10.12	8.65	84.76
NIKKEI	12.22	12.34	11.80	11.85	12.70	12.82	16.12	10.14	83.88
SHANGHAI	11.59	11.68	11.37	11.29	11.55	11.87	11.45	19.19	80.81
TO	90.61	91.76	84.56	86.17	86.43	94.21	72.22	63.40	669.36
Inc.Own	106.09	107.22	100.79	102.11	103.40	109.44	88.34	82.59	
NET	6.09	7.22	0.79	2.11	3.40	9.44	-11.66	-17.41	**83.67**

Panel C. Return connectedness at the upper tail (τ = 0.95)

τ = 0.95	OMX H25	OMX S30	OMX C20	OBX O20	S&P 500	STOXX 600	NIKKEI	SHANG HAI	FROM
OMXH25	16.05	14.30	12.32	12.95	11.84	14.27	9.62	8.64	83.95
OMXS30	14.29	16.05	12.38	12.82	11.87	14.54	9.60	8.46	83.95
OMXC20	13.03	13.11	17.00	12.72	11.51	13.71	10.00	8.94	83.00
OBXO20	13.47	13.25	12.48	16.68	11.59	13.74	9.99	8.80	83.32
S&P 500	12.72	12.99	11.82	12.21	17.42	13.64	10.10	9.09	82.58
STOXX 600	13.98	14.28	12.69	12.99	12.33	15.78	9.62	8.33	84.22
NIKKEI	12.15	12.06	11.59	11.88	11.89	12.42	17.67	10.34	82.33
SHANGHAI	11.43	11.12	11.24	11.22	10.79	11.23	11.77	21.21	78.79
TO	91.07	91.12	84.51	86.78	81.82	93.54	70.70	62.61	662.15
Inc.Own	107.13	107.17	101.50	103.47	99.23	109.32	88.37	83.82	
NET	7.13	7.17	1.50	3.47	-0.77	9.32	-11.63	-16.18	**82.77**

Figure 7 plots the static network of return connectedness among markets at three distinct quantiles. The direction and thickness of the arrows represent the direction and magnitude of return spillovers, respectively. Markets shaded in yellow are identified as net receivers, while those in blue are net transmitters. Under normal market conditions, the system shows relative interdependence. However, at both lower and upper quantiles, the network becomes significantly denser, reflecting more substantial and more widespread return spillovers during periods of extreme market movements. It can also be observed that while Europe, Sweden, and Finland act as dominant transmitters of shocks, Japan and China function as primary receivers of shocks. The network also reveals that some markets shift roles across different quantiles.

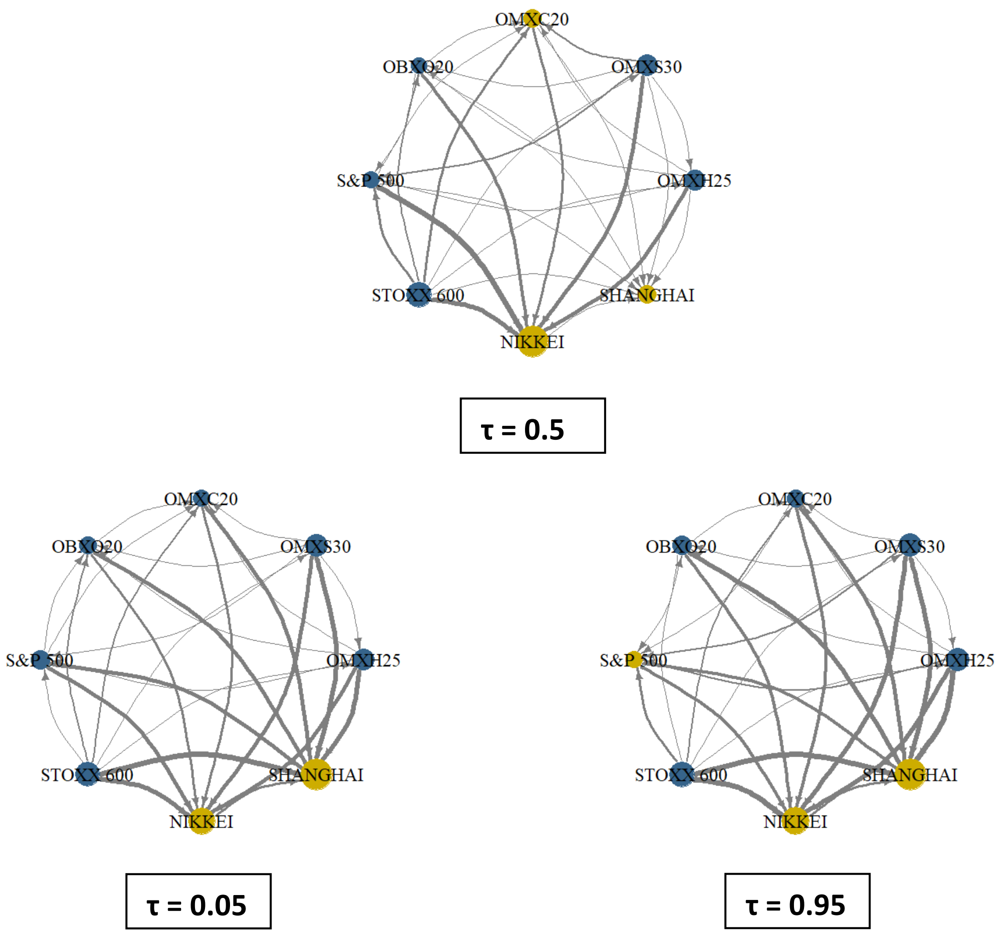

Figure 7. Network of return connectedness at three quantile levels

5.2.2 Dynamic connectedness analysis

To investigate the dynamic network connectedness among Nordic and other major global stock markets, this study runs the QVAR(1) model with a 200-day rolling window and a 10-day-ahead forecast horizon. The analysis is conducted at three different quantiles: the median and the two tails of return distributions. This enables us to explore the changes in connectedness across time and under different market conditions, namely normal, bearish, and bullish markets. The results for the total connectedness index (TCI) are retrieved and plotted in Figure 8. The considerable fluctuations in TCI values indicate that the level of return connectedness is highly sensitive to major global events. Overall, the TCI of returns at the median quantile, shown in blue, remains at a relatively high level, generally above 40, and exhibits time-varying characteristics. It exhibits pronounced spikes during major global turbulences. The first major increase occurs during the Global Financial Crisis (2007-2009), with the TCI reaching approximately 70%. The second peak appears around the European Sovereign Debt crisis (2011-2012), a period that also coincides with notable extreme weather events, then drops dramatically. The third surge is observed around the time of the Brexit referendum (2016). The most prominent spike occurs during the COVID-19 pandemic (2020), when the TCI at the median quantile climbs to its highest level at 75%. Another recent increase in TCI is related to Russian-Ukrainian tensions (2022), but the increase is less substantial compared to previous peaks. These spikes illustrate the strong interdependence among markets during periods of rising uncertainty and stress, as global shocks amplify return spillovers. Specifically, the TCI values at the median quantile tend to approach around 70% during these turbulent periods, compared to average levels of around 55% during stable periods.

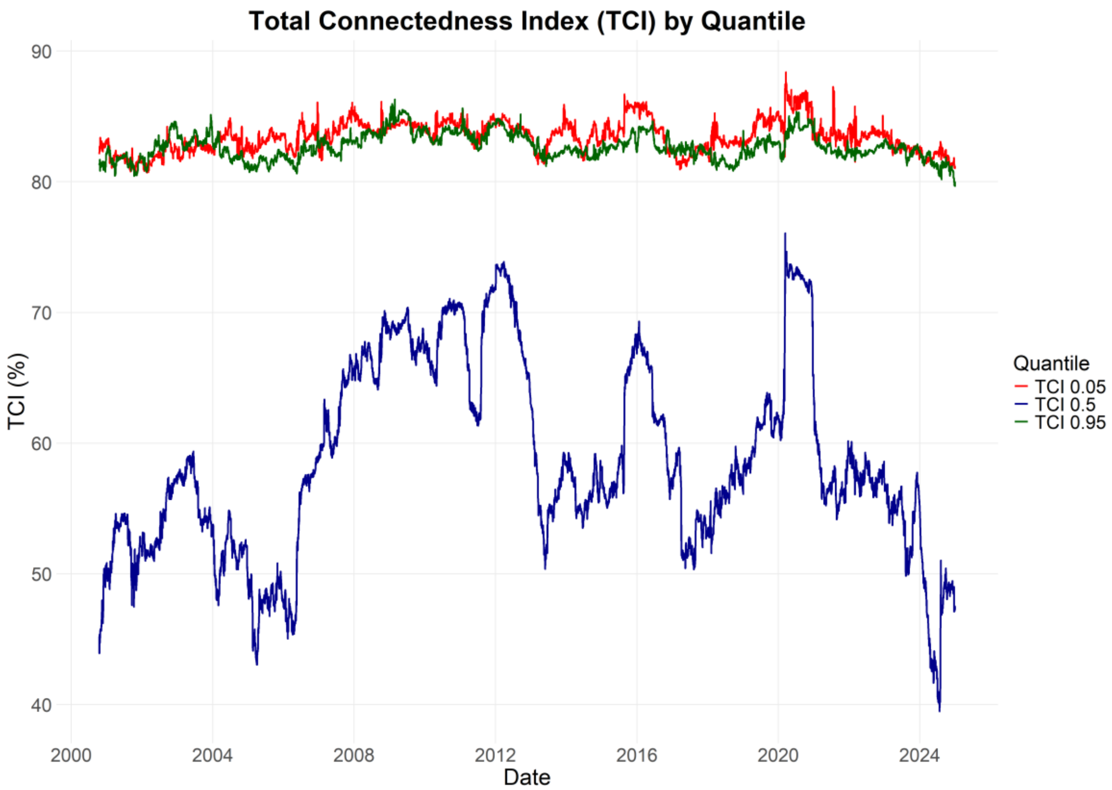

Figure 8. Dynamic Total Connectedness Index (TCI) of returns across time at three quantile levels using a 200-day rolling window

Regarding the TCI values at different quantile levels, it is observed that the TCI at the extreme lower quantile (red line) and upper quantile (green line) are consistently higher than that at the median quantile (blue line), with values remaining above 80% throughout the sample period. This clearly indicates that return spillovers intensify at both tails of the distributions, reflecting intensified market linkages during periods of extreme negative (bearish) and positive (bullish) conditions. In such regimes, information originating in one market tends to be transmitted more quickly and widely to others within the system. The findings are consistent with prior studies (Lorente et al., 2023; Urom & Ndubuisi, 2023; Lang et al., 2024; Hoque et al., 2024). Moreover, the lower tail TCI values are often slightly higher than the upper tail TCI values, indicating that systemic connectedness tends to be stronger during downtrends than uptrends. This asymmetry aligns with previous findings that markets exhibit stronger comovements during crises, driven by contagion effects and increased investor risk aversion (Urom & Ndubuisi, 2023; Basher & Sadorsky, 2024). While positive news in bullish periods may foster coordinated market optimism, negative news during bearish episodes can trigger widespread risk transmission. The latter particularly emphasizes the need for proactive portfolio rebalancing and robust risk management strategies during market downturns to mitigate the impact of amplified spillover effects.

Furthermore, to gain more insight into the changing total spillover across various quantiles, we estimate the value of TCI at multiple quantile levels. **Figure 9** presents TCI values computed using the QVAR(1) model with a 200-day rolling window and a 10-day forecast horizon. The figure illustrates how the level of systemic return connectedness varies under different market conditions, ranging from extreme downturns (left tail) to extreme upswings (right tail). The TCI exhibits a U-shaped pattern across quantiles. Specifically, the TCI reaches its highest levels at the tails - both at the 5th and 95th percentiles – exceeding 80%, implying that return spillovers intensify during periods of recession and expansion. This confirms that market interdependence is more pronounced under extreme conditions, a result that aligns with the literature on stronger co-movements in both crises and speculative booms. In contrast, the TCI gets its lowest value, above 50, at the median quantile (50th percentile). This value indicates weaker transmission of shocks across the network when volatility and sentiment are moderate. Taken together, the quantile-dependent pattern confirms that connectedness is state-dependent and asymmetric, with systemic risk peaking under both burst (left tail) and boom (right tail), but diminishing under normal market regimes. Therefore, it is important to analyze the return connectedness among Nordic and major equity markets across the entire distribution, rather than focusing solely on the average condition.

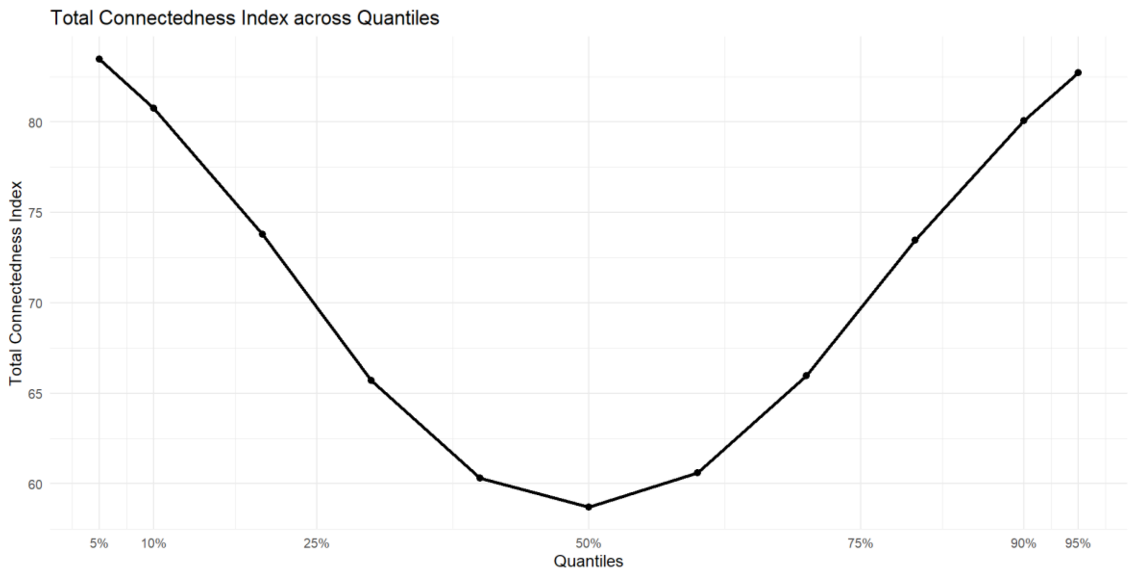

Figure 9. Quantile-based TCI of returns using QVAR(1) with a 200-day window length and a 10-day ahead forecast

Figures 10, 11, and 12 display the time-varying net connectedness of Nordic and other stock indices over a twenty-five-year period. Similar to the TCI calculation, these results are estimated using the QVAR(1) model, employing a selected 200-rolling window and a 10-day-ahead horizon. The connectedness is conducted across three different quantiles of return distributions: median (τ = 0.5), lower (τ = 0.05), and upper (τ = 0.95), representing normal, bearish, and bullish market conditions, respectively. These figures illustrate the dynamic roles that each market plays as a net transmitter or net receiver of return spillovers across various market regimes.

Across three quantiles, individual markets exhibit substantial fluctuations in their net connectedness. At the median quantile, Finland (OMXH25) and Sweden (OMXS30) exhibit more frequent and consistent positive values, indicating relatively persistent transmission of shocks. Denmark (OMXC20) and Norway (OBXO20), however, usually fluctuate around the zero line, shifting between being net transmitters and receivers over time. Notably, over the past three years, both countries have had negative net values, indicating a more passive role in absorbing rather than spreading market shocks. Among the major global indices, the U.S market (S&P 500) shows spikes in net transmission, interestingly peaking in 2018 when the escalating U.S.-China trade war chilled business confidence and raised uncertainty. The broad European market (STOXX 600) continues to exhibit steady positive net connectedness, confirming its role as a key transmitter of shocks within both the Nordic region and the broader European equity landscape. Asian markets, on the other hand, tend to act as net receivers of shocks. Before 2007, the Chinese market (SHANGHAI) appears relatively neutral, but after 2007, its net connectedness turns more negative. Surprisingly, the Japanese market (NIKKEI) absorbs a large portion of global spillovers, with net values occasionally approaching -60%, highlighting its strong role as a systemic shock absorber during periods of global stress.

With respect to extreme negative and positive return conditions, the net connectedness sometimes experiences temporary but sharp spikes or drops, particularly during periods of tensioned geopolitical or financial crises. Although the values of net connectedness for the four Nordic countries are relatively lower under extreme conditions compared to normal regimes, they nonetheless experience transient but significant shifts at some point in time. Particularly, Finland tends to lean more toward net receivers during crises, while Denmark also continues to act as a receiver during market rallies. In the meantime, the U.S., Europe, and Sweden primarily arise as key shock transmitters during both bearish and bullish market phases. Asian markets remain consistent net receivers, confirming their vulnerability to external shocks. However, the negative net values for Japan are less evident in both tails than in the normal quantile, suggesting a slightly reduced shock absorption role during extremes. Conversely, the value of China's net connectedness increases considerably, emphasizing its growing sensitivity and vulnerability to global market dynamics under extreme return conditions. Overall, during volatile market phases, Sweden generally maintains its position as a transmitter of shocks. Finland, in contrast, transfers from a transmitter under normal conditions to a receiver during periods of extreme downturns. Denmark exhibits more fluctuation but tends to act as a receiver across all market regimes. Norway, meanwhile, appears relatively more resilient, with its net values remaining close to zero, particularly during bullish phases, indicating a more neutral role in the transmission network. These findings align with prior studies, which show that developed markets tend to transmit shocks, while developing markets absorb them (Hoque et al., 2024; Guo et al., 2024; Cao, 2025).

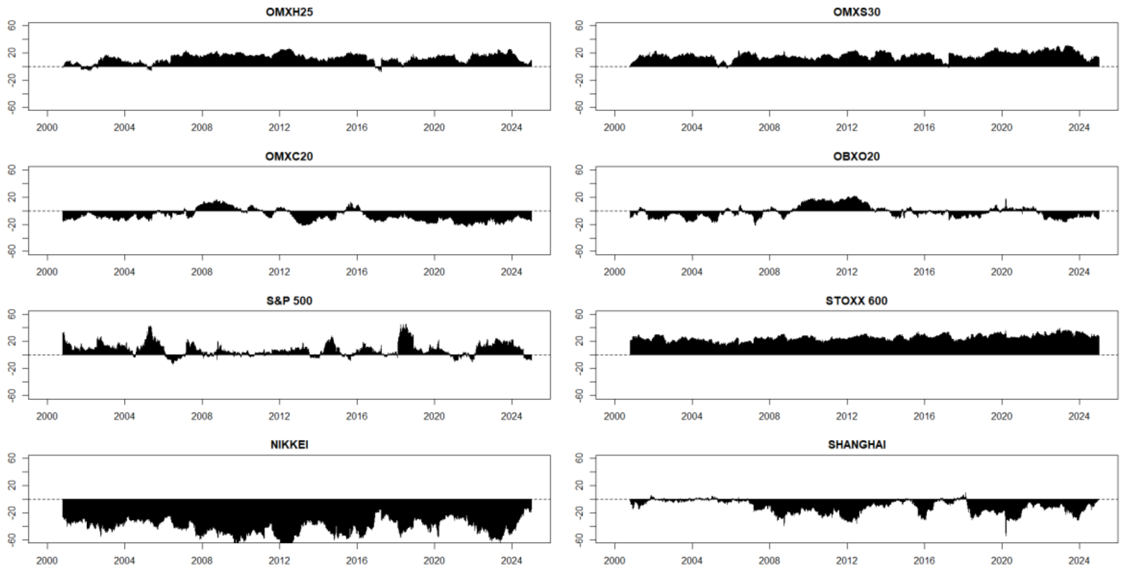

Figure 10. Time-varying NET connectedness at the median quantile

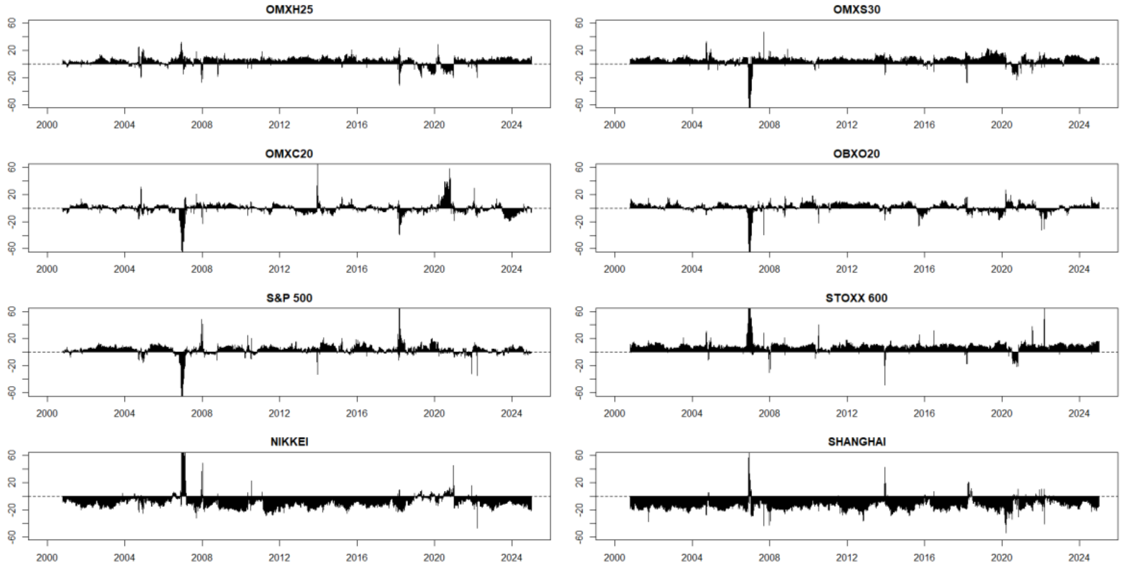

Figure 11. Time-varying NET connectedness at the lower quantile

Panel of time-series plots showing time-varying net connectedness of eight stock markets at the median quantile

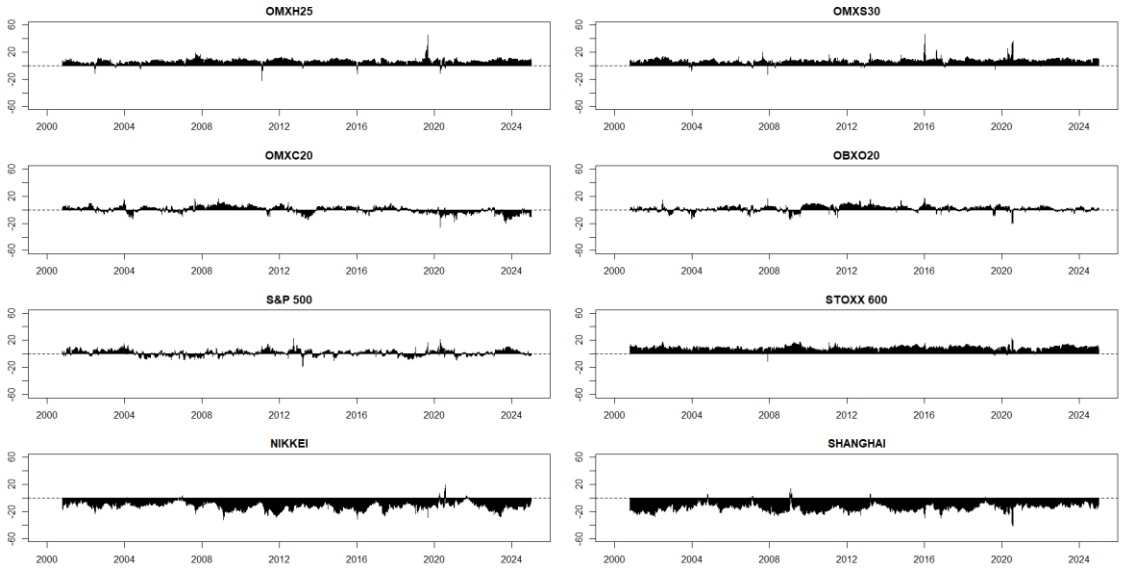

Figure 12. Time-varying NET connectedness at the upper quantile

To assess the robustness of the return connectedness dynamics, Figure 13 shows TCI over time across three quantile levels using a 100-day rolling window. This shorter window, compared to the 200-day baseline, enables a more responsive capture of rapid changes in market linkages. The results reinforce earlier findings when showing that the TCI at the median quantile (blue line) displays significant time variation, with remarkable spikes aligning with major global financial events such as the Brexit referendum (2016) and the COVID-19 pandemic (2020). A moderate increase is again observed around the Russia–Ukraine conflict in 2022. Moreover, the constant high level of TCI values at the lower and upper quantiles (red and green lines, respectively), which fluctuates above 80%, further strengthens the asymmetric and state-dependent nature of markets under extreme conditions. These results reinforce the conclusion that systemic connectedness intensifies during periods of tail risks, regardless of the rolling window length.

Line chart showing the Dynamic Total Connectedness Index (TCI) of stock market returns over time from 2000 to 2024, calculated using a 200-day rolling window

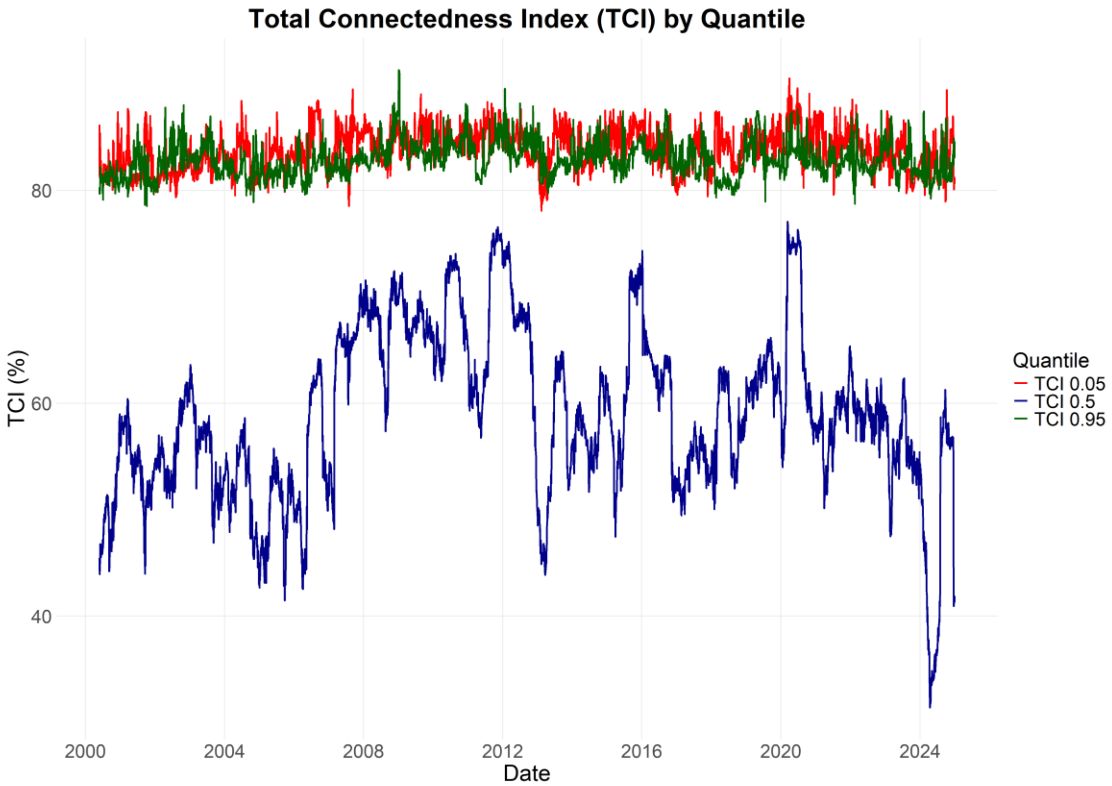

Figure 13. Dynamic Total Connectedness Index (TCI) of returns across time at three quantile levels using a 100-day rolling window

5.3 Impacts of climate risks on market interdependence

In the second phase of our study, we examine the impact of climate risks on the Total Connectedness Index (TCI) obtained from the Quantile Vector Autoregression (QVAR) model in the first phase. The objective is to assess whether variations in climate risks are associated with changes in the degree of stock market linkages.

5.3.1 Data description

Table 3 reports descriptive statistics for the TCI values at the median quantile ($\tau = 0.5$), using two rolling window lengths: TCI 100 (based on a 100-day rolling window) and TCI 200 (based on a 200-day rolling window). In addition, two climate risk proxies and three uncertainty proxies are presented, including the Transition Risk Index (TRI), Physical Risk Index (PRI), VSTOXX (a measure of market volatility), the UK Economic Policy Uncertainty Index (EPUK), and the Daily Geopolitical Risk Index (GPRD). The dataset spans the period from 2005 to 2023, yielding 4,082 daily observations for each variable. Statistical values include mean, standard deviation, minimum, maximum, skewness, kurtosis, Jarque-Bera (JB) test for normality, and Augmented Dickey-Fuller (ADF) test for stationarity.

The mean values of TCI 100 and TCI 200 are approximately 61 and 60.7, respectively, suggesting a relatively high connectedness within the system. Despite different rolling windows, the average TCI values are nearly similar. The standard deviation of TCI 100 is slightly higher than that of TCI 200, implying that the short-term connectedness measure exhibits more frequent fluctuation. The skewness and kurtosis values for both TCI indices are close to a normal range, indicating near-symmetric distributions with light tails. However, the JB test statistics are statistically significant at the 1% level, leading to the rejection of the null hypothesis of normality for both TCI series. Regarding stationarity, the ADF test indicates that TCI 100 is stationary at the 5% significance level, while TCI 200 fails to meet the critical threshold, suggesting possible non-stationarity. Based on these results, the TCI 100 series is selected as the dependent variable in the subsequent regression analysis to represent the dynamic level of network linkage across equity markets.

In terms of climate risk measures, both TRI and PRI have mean values near zero. However, they show considerable skewness and excess kurtosis, particularly in the TRI, which is positively skewed with a high kurtosis value of 7.53, indicating a heavy-tailed distribution. The highest observed values for the TRI and PRI are 19.1% and 12.3%, respectively, indicating periods of unusually elevated attention to transition and physical climate risks. Figure 14 and Figure 15 show the scatter plots of the daily physical risk index and transition risk index. Positive, zero, and negative values of these indicators reflect periods of heightened, average, or diminished discussion surrounding climate risk issues. As the TRI and PRI are derived as residuals from an AR(1) process applied to the underlying concern series, they can be interpreted as representing positive, neutral, or negative shocks to the level of climate-related risks.

Table 3. Descriptive statistics for TCI (τ = 0.5), climate risk, and uncertainty proxies

	Obs	**Mean**	**Std.dev**	**Min**	**Max**	**Skew**	**Kurtosis**	**JB test**	**ADF test**
TCI 100	4082	60.982	7.265	41.458	77.069	0.006	2.493	44***	-4.40**
TCI 200	4082	60.700	7.037	43.050	76.066	0.037	2.224	103***	-2.62
PRI	4082	0.001	0.021	-0.056	0.123	0.775	4.482	782***	-10.25**
TRI	4082	0.001	0.024	-0.078	0.191	1.053	7.530	4244***	-9.74**
VSTOXX	4082	22.393	8.905	10.678	87.513	2.093	10.110	11579***	-5.43**
EPUK	4082	306.433	192.156	0.000	2610.1	1.841	11.573	14804***	-5.98**
GPRD	4082	106.4352	45.875	9.492	540.83	2.321	14.886	27693***	-8.243**

Note: ***, ** indicates the null hypothesis is rejected at the 1% and 5% significance level

The three uncertainty variables included in the analysis are VSTOXX, EPUK, and GPRD. Among them, GPRD shows the highest skewness (2.3) and kurtosis (14.9), indicating the presence of extreme values and asymmetric distributions, which are likely driven by sudden geopolitical shocks or conflict events. To stabilize volatility and reduce heteroscedasticity, we take the natural logarithm of the EPUK and GPRD variables before including them in the regression analysis. According to the ADF test, all three uncertainty proxies reject the null hypothesis of a unit root at the 5% significance level, confirming that the series are stationary and suitable for time-series modeling.

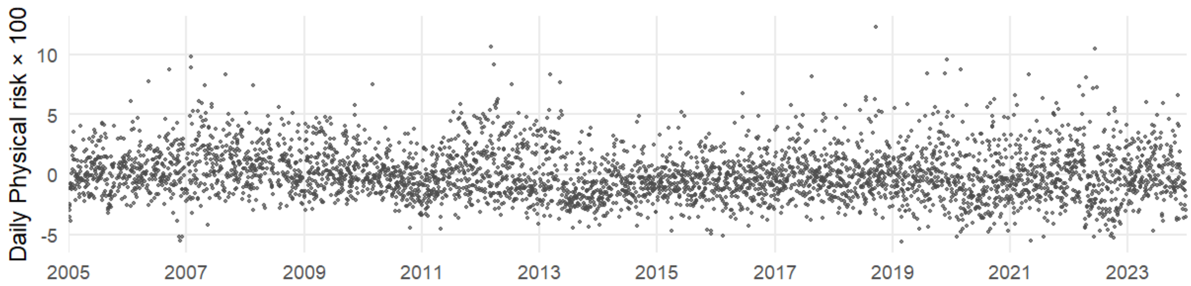

Figure 14. Daily Physical Risk

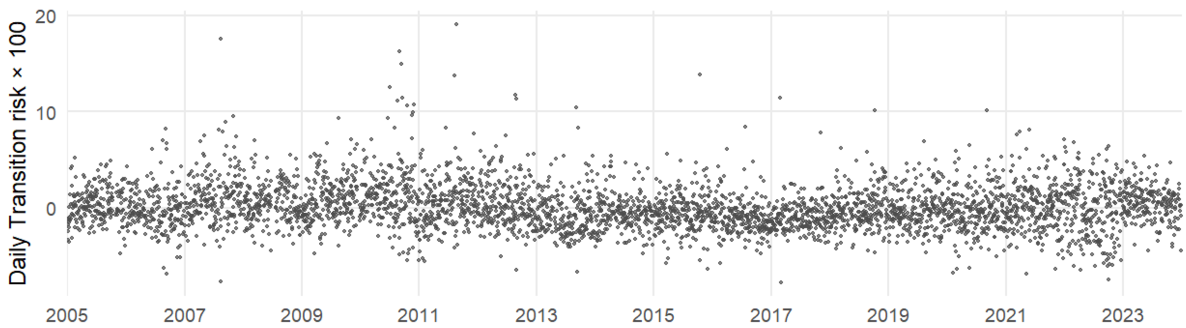

Figure 15. Daily Transition Risk

Figure 16 shows the pairwise correlation matrix between the two TCI measures (TCI 100 and TCI 200), climate risk indicators (TRI and PRI), investor sentiment (VSTOXX), the economic policy index (EPUK), and the geopolitical risk index (GPRD). As shown in the figure, the correlation coefficient between TCI values, calculated using 100-day and 200-day rolling windows, respectively, under normal market conditions, is 0.83 and is statistically significant at the 1% level. This strong linear relationship is visually confirmed in the scatter plot, where observations are tightly clustered around the diagonal line. The correlation coefficient between the two climate risk indicators (TRI and PRI) is 0.36, implying that transition and physical risks co-move to some extent. However, the PRI exhibits near-zero correlation with both TCI 100 and TCI 200, suggesting that physical climate risks do not systematically influence financial market connectedness. In contrast, the TRI shows a small but statistically significant positive correlation with both TCI measures, implying that intensified transition risk is slightly associated with increased market interdependence. This likely supports the hypothesis that transition risk functions as a transmission mechanism in financial markets, particularly through more immediate regulatory and policy-driven changes.

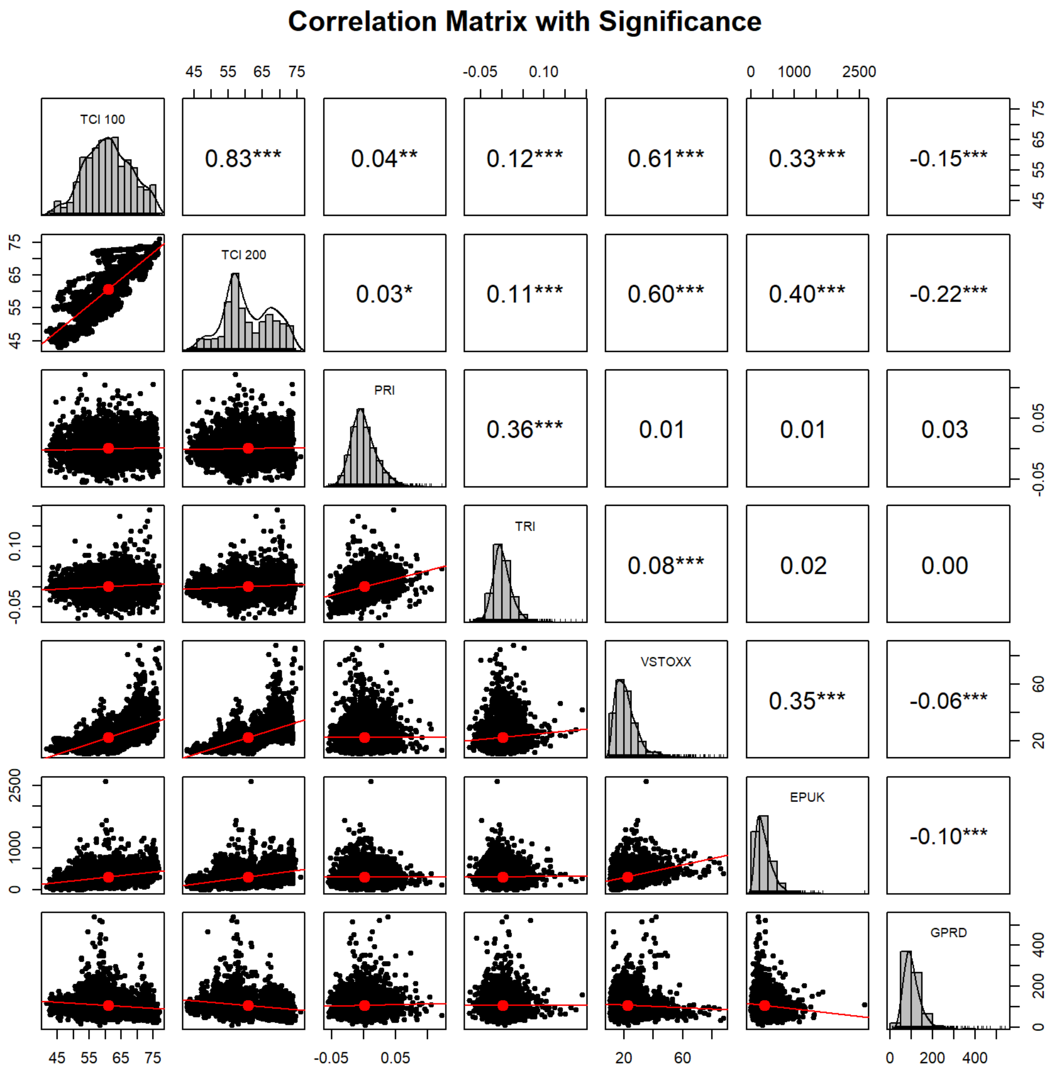

Figure 16. Correlation coefficient matrix of TCI, Climate risks, and Uncertainty variables

Note: *p<0.1; **p<0.05; ***p<0.01

There are strong and statistically significant correlations above 0.6 between the volatility index (VSTOXX) and TCI values. This shows that anticipated future market volatility is closely tied to the level of financial interdependence, consistent with the notion that uncertainty amplifies interdependence across markets. The EPUK also exhibits a statistically significant and positive correlation with both the TCI 100 and the TCI 200, suggesting that regional policy uncertainty can have implications for market integration on both regional and global scales. Surprisingly, the GPRD displays a small but statistically significant negative correlation with the TCI values and two other uncertainty metrics. This may imply that rising geopolitical tensions contribute to market disintegration or risk aversion, thereby weakening market linkages during periods of geopolitical stress.

To further investigate the effects of market sentiment, economic policy uncertainty, and geopolitical risk, we visualize the fluctuations of TCI values in the middle quantile with two different rolling windows to measure the short-term and long-term market connectedness. The visualizations are shown in **Figure 17**, **Figure 18** and **Figure 19**, respectively. The connectedness values are represented by the dark blue (TCI 100) and the light blue (TCI 200) lines, while the VSTOXX is shown in red (**Figure 17**), the EPU in yellow (**Figure 18**), and the GPR in orange (**Figure 19**). The VSTOXX is commonly regarded as the ”fear gauge” index, where a high value indicates greater expected market uncertainty. As shown in **Figure 17**, VSTOXX reaches its historical peaks during two major crisis periods - the 2008 GFC and the 2020 COVID-19 pandemic. Another visible spike occurred following the start of the Russia–Ukraine war in 2022. These spikes in the VSTOXX are accompanied by noticeable increases in TCI values, suggesting a close association between high sentiment and strong market linkages. Besides, while the VSTOXX series displays high-frequency fluctuations and reacts promptly to market events, the TCI series appears relatively smoother and more persistent over time. This is likely due to the nature of the rolling window estimation in TCI values, which grasps gradual shifts in systemic interconnectedness rather than immediate short-term shocks. These visual patterns support the hypothesis that rising investor uncertainty tends to amplify cross-market linkages.

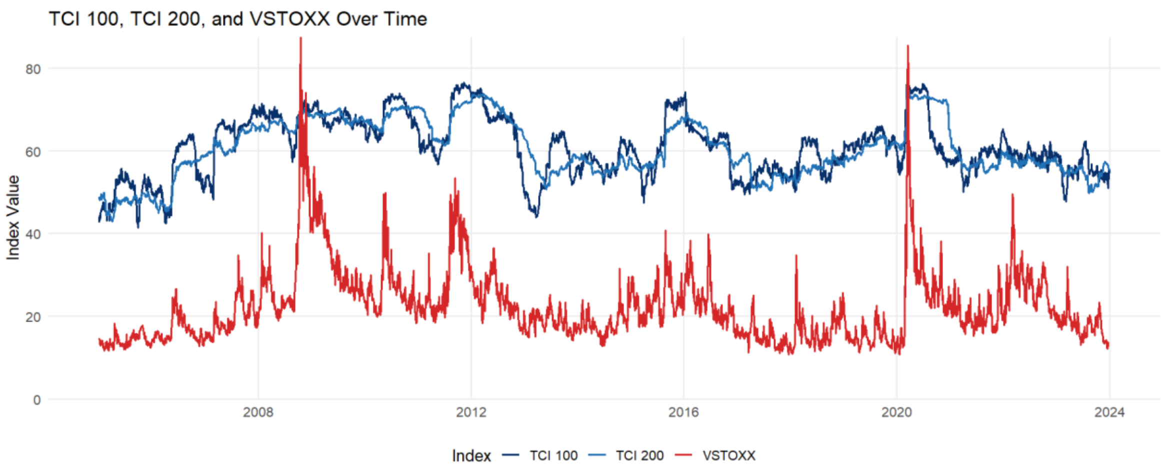

Figure 17. TCI (τ = 0.5) and VSTOXX 50 over time

In **Figure 18**, the EPU index represents news-based measures of economic policy uncertainty, which has gained prominence for its effectiveness in capturing major economic and political developments. This index tends to surge amid enduring geopolitical risk and rising uncertainty surrounding economic policy. A notable feature is the narrowing gap between market linkages and economic policy uncertainty, particularly during periods of intense systemic stress. During such episodes, spikes in connectedness often align with prominent policy uncertainty. Within the past decade, the most pronounced EPUK peaks are observed in 2016 (Brexit referendum), 2020 (COVID-19 pandemic), and 2022 (Russia–Ukraine war). In many instances, sharp increases in EPUK occur alongside upward movements in both TCI 100 and TCI 200, suggesting that economic policy uncertainty is associated with tighter market interdependence. Unlike the relatively smooth and persistent behavior of the TCI series, due to their rolling-window construction, EPU is highly reactive and prone to sharp, event-driven spikes. This is reflected in the wide range between its minimum (0) and maximum (2610), indicating its sensitivity to major shocks and its role as a high-frequency indicator of uncertainty.

Regarding geopolitical risk, investors must navigate several geopolitical threats that can profoundly impact financial markets. Apart from political uncertainty, geopolitical tensions remain among the top concerns for market participants. The GPR index quantifies such risks based on the frequency and content of international newspaper archives. Higher values indicate escalated global geopolitical tensions. As illustrated in **Figure 19**, the GPR index exhibits sharp spikes during periods of well-known geopolitical events. These spikes tend to be short-lived but extreme, with the highest recorded value at 540.83 compared to the minimum value at 9.49. While some temporal overlap exists between spikes in geopolitical risk and increases in TCI, the correlation appears weak or even negative in many periods.

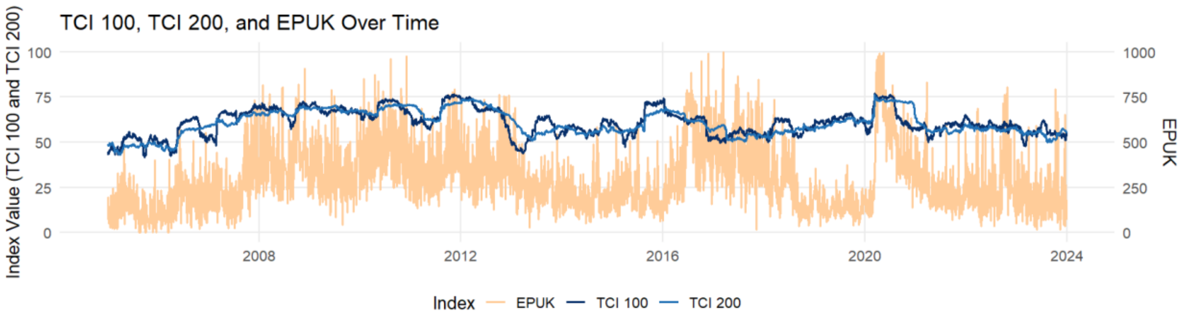

Figure 18. TCI (τ = 0.5) and EPU over time

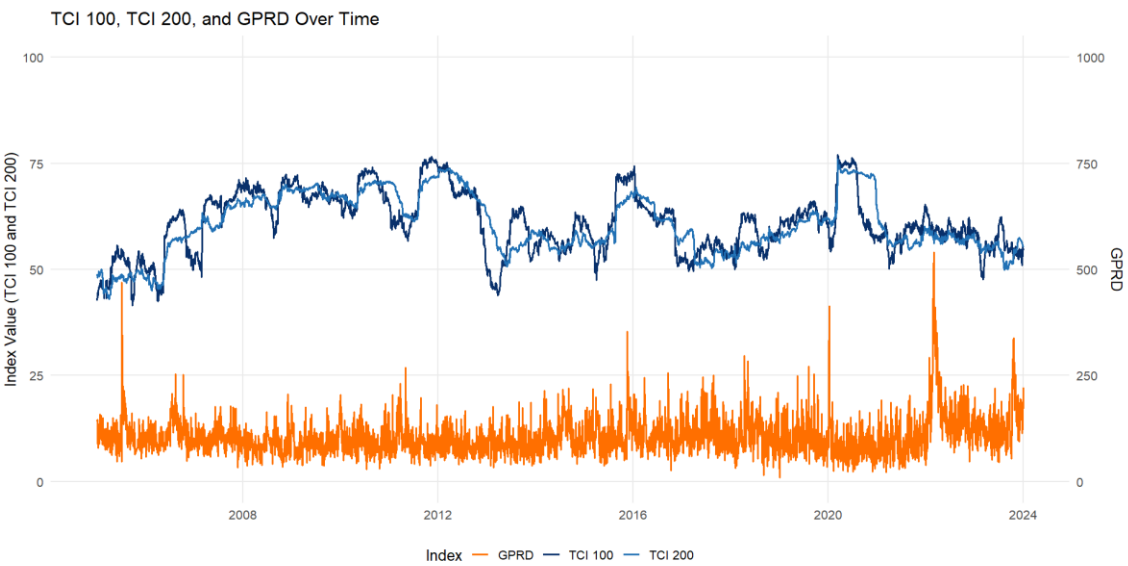

Figure 19. TCI (τ = 0.5) and GPR over time

5.3.2 Regression results

We perform OLS regressions with TCI 100 values as the dependent variable, which serves as a proxy for market interdependence. Each factor is treated as an independent variable affecting market linkages. Initially, we estimate bivariate regressions under normal market conditions (using TCI 100 at the median quantile), where each explanatory variable is regressed separately against TCI (from Model 1 to Model 5). Subsequently, we conduct multivariate regressions (Model 6 to Model 8) that include all explanatory variables across three stock market states (using TCI 100 at the median, lower, and upper quantiles, respectively). Table 4 reports the regression results under the stable scenario, while Table 5 shows the findings for three market conditions.

Across regression models, most explanatory variables have statistically significant effects on market interdependence. One exception is the Physical Risk Index (PRI), which, although positive and significant in the bivariate regression under normal conditions, becomes insignificant in the multivariate models. This suggests that the influence of physical risks is not robust when controlling for other risk factors. TRI, on the other hand, consistently maintains a strong and statistically significant positive relationship with TCI in both normal and bear market conditions. This supports the hypothesis that transition risks increase return connectedness among regional and global markets. However, it is worth noting that the magnitude of TRI's effect is substantially smaller under bear market conditions, indicating a minor response during periods of market stress. Interestingly, the role of TRI as a meaningful determinant of market connectedness diminishes during bull markets, suggesting that climate-related concerns are not prioritized in periods of strong market optimism. These findings support the evidence presented by Hoque et al. (2024), which documents a positive correlation between climate change attention and market integration. Similarly, the study of Basher and Sadorsky (2024) reports that concerns about global warming have a positive and significant impact on systemic risk during both bear and normal market regimes, while climate-related international summits are associated with reduced systemic risk under stable conditions. Nevertheless, their study also highlights that the overall magnitude of climate-related impacts remains relatively small, especially when compared to the more substantial effects of other factors.

Table 4. Regression results for TCI under median quantile

OLS Results for TCI 100 at the median quantile

	PRI	**TRI**	**VSTOXX**	**EPUK**	**GPRD**	**Full Model**
	(1)	**(2)**	**(3)**	**(4)**	**(5)**	**(6)**
PRI	0.146***					0.046
	(0.054)					(0.045)
TRI		0.371***				0.210***
		(0.048)				(0.039)
VSTOXX			0.501***			0.442***
			(0.010)			(0.011)
EPUK				3.825***		1.705***
				(0.153)		(0.135)
GPRD					-3.041***	-1.554***
					(0.291)	(0.228)
Constant	60.974***	60.952***	49.768***	39.821***	74.973***	48.778***
	(0.114)	(0.113)	(0.243)	(0.854)	(1.342)	(1.326)
Observations	4,082	4,082	4,082	4,082	4,082	4,082
R^2	0.002	0.015	0.377	0.133	0.026	0.414
Adjusted R^2	0.002	0.014	0.377	0.132	0.026	0.413
F Statistic	7.195***	60.513***	2,466.59***	623.308***	109.521***	575.781***
Note:						*p<0.1; **p<0.05; ***p<0.01

PRI and TRI are multiplied by 100; EPUK and GPRD are modified by taking the natural logarithm of EPUK and GPRD

Table 5. Regression results for TCI across three varied quantiles

OLS Results for TCI 100 at different quantiles

	Median quantile	**Lower quantile**	**Upper quantile**
	(6)	**(7)**	**(8)**
PRI	0.046	-0.007	-0.009
	(0.045)	(0.014)	(0.012)
TRI	0.210***	0.029**	0.005
	(0.039)	(0.012)	(0.010)
VSTOXX	0.442***	0.058***	0.058***
	(0.011)	(0.003)	(0.003)
EPUK	1.705***	0.037	0.249***
	(0.135)	(0.041)	(0.035)
GPRD	-1.554***	-0.187***	-0.200***
	(0.228)	(0.069)	(0.059)
Constant	48.778***	83.552***	81.331***
	(1.326)	(0.404)	(0.345)
Observations	4,082	4,082	4,082
R^2	0.414	0.096	0.153
Adjusted R^2	0.413	0.094	0.152
F Statistic	575.781***	86.123***	147.770***
Note:			*p<0.1; **p<0.05; ***p<0.01

TRI and PRI are multiplied by 100; EPUK is modified by taking the natural logarithm of EPUK and GPRD

In terms of market sentiment, the VSTOXX index constantly demonstrates a positive correlation with network linkages at the highest level of significance. This indicates that an increase in the market's expectation of volatility is strongly linked to greater market connectedness, consistent with prior findings that investor sentiment amplifies return spillovers. In normal market conditions, a one-standard-deviation increase in VSTOXX raises systemic connectedness by 4%. In line with previous studies (Basher & Sadorsky, 2024; Hoque et al., 2024; Wan et al., 2024), these results prove that the sentiment indicator is a key determinant of market integration strength. Similarly, the Economic Policy Uncertainty Index (EPUK) is positively correlated with TCI levels in normal and extreme upside market conditions. These findings underscore the relevance of policy-related uncertainty, as expectations regarding economic policy directions appear to contribute to stronger financial interconnectedness. The findings support conclusions in earlier works (Basher & Sadorsky, 2024; Hoque et al., 2024; Wan et al., 2024). Conversely, the Geopolitical Risk Index (GPR) continues to show an adverse effect on TCI at a 1% significance level. These results suggest that geopolitical tensions tend to undermine, rather than reinforce, global financial integration, likely due to increased investor risk aversion and capital reallocation away from vulnerable markets. While these results align with the findings of Hoque et al. (2024), they challenge the contrasting evidence reported by Urom & Ndubuisi (2023), which claims that geopolitical risk can act as a pull factor during periods of extreme bullish market conditions.

6 CONCLUSION

6.1 Implications

This thesis examines the dynamic return connectedness among Nordic and major global stock markets using a Quantile Vector Autoregression (QVAR) framework, estimated across three different market states—normal, bearish, and bullish—using both a 200-day and a 100-day rolling window, as well as a 10-day-ahead forecast horizon. The Total Connectedness Index (TCI) values and NET spillover measures reveal a high level of connectedness within the network, averaging around 60%. Importantly, this connectedness intensifies steadily and reaches above 80% during both quantile tails, particularly at the lower quantile, showing asymmetric patterns. The U-shaped TCI pattern across quantiles - peaking at the 5th and 95th percentiles - indicates that market interdependence increases significantly in both bearish and bullish markets, compared to more moderate transmission during normal conditions. Another finding is that connectedness spikes during global crises such as the GFC (2007–2009), European Sovereign Debt Crisis (2011–2012), Brexit referendum (2016), and the COVID-19 pandemic (2020), confirming that return spillovers are most intense during turbulent periods. These results highlight the conditional and nonlinear nature of market linkages, emphasizing the importance of accounting for varying market regimes in risk management and portfolio allocation.

With respect to each market, the U.S., leading European stocks, and Sweden play a dominant role as consistent net transmitters of return shocks. In contrast, Denmark and Asian markets, such as Japan and China, act more as shock absorbers. Notably, China exhibits increased net connectedness during tail events, indicating its growing systemic relevance under extreme market conditions. Finland serves as a transmitter but occasionally shifts to a net receiver during times of crisis. Norway, on the other hand, remains relatively resilient throughout the sample period, exhibiting limited net spillover activity and generally not assuming a pronounced role as either a transmitter or a receiver. These differentiated roles across markets emphasize the heterogeneity in return spillover dynamics and highlight the importance of regional and market-specific factors in shaping interconnectedness patterns.

This study further explores the determinants of market interdependence by incorporating two dimensions of climate risks (physical and transition), together with investor sentiment, and broader uncertainty factors (economic policy and geopolitical risks). These variables are included as explanatory and control variables. The TCI values, estimated at three different quantiles, are used to measure network connectedness. Results from OLS regression models indicate that physical risks (PRI) show a positive correlation in bivariate settings, but lose significance in multivariate models, suggesting physical risk has limited explanatory power when controlling for other variables. This finding suggests that physical risks are not yet clearly priced into financial markets, potentially due to their long-term and uncertain nature. In contrast, transition risks (TRI) and market sentiment (VSTOXX) are consistently associated with higher connectedness, particularly under normal and bearish conditions. Although the estimated coefficients for TRI are relatively modest, their statistical significance suggests that transition risks represent an important transmission channel for financial shocks. Besides, the findings support the idea that high investor sentiment exacerbates systemic spillovers, particularly during periods of market turmoil. In terms of economic policy uncertainty (EPUK), the results indicate a significant positive impact of EPUK on TCI values in both normal and bullish states, identifying the importance of policy clarity and consistency in maintaining market integration. Interestingly, geopolitical risk (GPRD) has a negative and significant effect on connectedness, implying that increased geopolitical tensions can lead to fragmentation rather than cohesion among markets.

Therefore, these findings have critical implications for policymakers and market participants. From a policy standpoint, the findings emphasize the need for enhanced climate risk disclosures, particularly regarding transition risks, to enable accurate risk pricing and more informed investment decisions. The evidence also reveals the growing influence of climate-related news on financial markets, reinforcing the value of timely, transparent communication of climate risk information. Policymakers should further integrate forward-looking risk assessment frameworks that reflect the pricing of climate risks into capital market supervision. This involves embedding climate scenario analysis, stress testing, and climate-related risk oversight mechanisms into regulatory practices to strengthen the financial system's resilience to climate-related shocks. In addition, the observed role of investor sentiment also underlines the importance of transparent communication during periods of market uncertainty to minimize contagion and herding behavior. From the perspectives of investors and asset managers, the findings emphasize the need for portfolio strategies that are adaptable to different market regimes. Given that the level of market connectedness varies significantly across market states, with correlations intensifying during periods of stress, traditional diversification becomes less effective precisely when it is most needed. Therefore, investment strategies should incorporate indicators of political, geopolitical, and climate-related uncertainty to enhance risk assessment and asset allocation. Furthermore, certain markets, such as the U.S. and leading European economies, consistently function as dominant transmitters of return fluctuations, exerting a substantial influence on other markets. Shocks originating in these leading markets can quickly propagate across borders, underscoring the need for robust risk prevention and monitoring mechanisms in more vulnerable economies. Market participants and policymakers in receiver markets should closely monitor developments in these leading economies to ensure timely adaptation to shifting global conditions. Finally, the findings indicate that the roles of individual markets are dynamic, with some shifting from net transmitters to net receivers, depending on the prevailing market state. This dynamic behavior reinforces the necessity for continuous, adaptive monitoring and flexible investment and regulatory strategies in response to evolving systemic risk patterns.

6.2 Limitations

Several limitations of this study should be acknowledged, which open avenues for future research and refinement.

First, while the Quantile Vector Autoregression (QVAR) model is well-suited to capture nonlinear dynamics across different quantiles, the use of a constantly rolling window in dynamic analysis presents a challenge in accurately representing extreme market conditions over specific periods. Consequently, the Total Connectedness Index (TCI) estimated at the lower or upper quantiles may not fully reflect true extreme periods if the corresponding time frame windows do not align with periods of high market tension.

Second, the use of linear OLS regressions may not fully reflect the complex, nonlinear relationships between systemic connectedness and climate or uncertainty variables. Given the overlapping nature of rolling quantiles in the TCI series and the use of daily data, short-term fluctuations are well addressed. However, key macroeconomic variables - typically reported at monthly or quarterly frequencies - may be underrepresented, potentially limiting the model's explanatory power.

Third, although this study primarily aims to assess connectedness among Nordic markets, it also considers the influence of other major global stock markets. The analysis relies on financial indices from regions with differing trading hours, which introduces temporal misalignment. This mismatch may impede the accurate capture of shock transmission, particularly across time zones. While ideally, a dataset based on overlapping or simultaneous trading periods would improve temporal alignment, constructing such a dataset poses practical challenges due to differences in market operation times.

Fourth, the climate risk proxies used - Physical Risk Index (PRI) and Transition Risk Index (TRI) - are constructed from the residuals of AR(1) processes applied to climate concern indices. While this methodology is innovative, it may not fully capture real-time climate-related stress or investor response. The inclusion of other climate risk indicators could enhance the robustness of the analysis.

Fifth, this study does not account for sectoral heterogeneity in climate risk exposure. Different sectors may respond differently to climate and uncertainty shocks - “brown” sectors may be adversely affected, while “green” sectors could benefit. Disaggregating the analysis by sector or incorporating sector-specific indices such as clean energy or ESG indices would offer deeper insights into the climate-finance nexus.

Lastly, this study does not consider heterogeneity among investor types, particularly between institutional and individual investors. Investor behavior and sentiment can vary significantly across these groups. Future research could explore sentiment dynamics and reaction functions by investor type, contributing to a more nuanced understanding of the behavioral transmission mechanisms underlying systemic connectedness.

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Appendices