# Resilience and Stability of Economic Networks - Essays in Complexity Economics

Inauguraldissertation

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# Contents

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# Chapter 1

# General Introduction

# 1 Introduction

*"It's honestly irresponsible to calculate around with some mathematical models that then don't really work" - Olaf Scholz.*[1]

This remark by the former Chancellor of Germany, Olaf Scholz, reflects broader tensions between economic expertise and political expectations. In my view, it highlights, on the one hand, the extent to which the credibility of the economics profession may suffer from historic overreliance on abstract modeling that fails to capture the complexities of real-world systems.[2] On the other hand, it also suggests that policymakers may seek unambiguous conclusions, even though economic models necessarily rely on assumptions, approximations and hence epistemic uncertainty. This dissertation presents three works employing three prominent methods in the realm of complexity economics. It concludes with a review that highlights how these approaches can support risk governance within economic policy, with the overarching aim of strengthening the resilience and stability of economic systems.

This introductory chapter serves as the foundation for the research. It introduces the key motivations behind the study and its relevance within the broader social and academic context. Additionally, this chapter offers a comprehensive overview of the work, outlining the primary objectives, research questions, and methodologies that guide the investigations.

## 1.1 Motivation and Objectives

My passion for economics is and has always been based on the idea of preserving and promoting social welfare. As we progress toward the end of the first quarter of the 21st century, numerous observers anticipate periods ahead marked by significant global risks. These risks are compounded by the world's intricate inter-dependencies, which create increasingly complex challenges for policymakers, such as global warming and political conflicts (see, e.g., Lawrence et al. (2024) or Rifkin (2022)).

[1] The quote can be found in Moll (2022, p. 2), in a transcript of the debate on the Anne Will show (Das Erste) on March 27, 2022. The context was a discussion about the economic implications of a sudden halt to Russian gas imports following the invasion of Ukraine, as well as assessments offered by economic experts.

[2] The study under discussion by Bachmann et al. (2022) was subsequently criticized, among others, by Krebs (2022) for using overly simplified behavioral assumptions and for neglecting propagation effects.

In my view, the active management of economic shocks and their propagation is crucial for several compelling reasons. First, unmanaged shocks can lead to significant social and human suffering, as economic downturns often disproportionately affect the most vulnerable populations. Second, unmitigated shocks can cause irreversible damage to the economy, resulting in a permanently lower long-term growth trajectory, as the economy fails to rebound fully from severe disruptions. Ultimately, even systemic failures are possible.

Proactive measures are crucial to ensure the stability and resilience of economic systems. Stability refers to an economic system's capacity to endure shocks, while resilience is the system's ability to recover from disruptions. A comprehensive understanding of risks and potential mitigation strategies can strengthen both. This includes analyzing how risks manifest as shocks, understanding the pathways through which these shocks propagate across interconnected networks, and developing coping strategies (International Risk Governance Center, 2018).

Effective governance requires adequate scientific consultation in a dynamic and increasingly interconnected world. In recent decades, the field of economics has evolved to better account for the complexities of the modern world. A new field of research known as complexity economics has emerged. It is based on the understanding of the economy as a complex dynamic system, also integrating insights from physics, psychology, and other disciplines (Arthur, 2015).

Systems can be understood as networks. Understanding their structure and network effects is key to managing economic risks and shocks. Nodes in networks are not homogeneous. In financial and goods markets, agents deviate in necessities and resources (e.g., stocks, funds, or information) as well as in processing abilities (e.g., capacities, efficiency, or rationality). Local features cause local tipping points. Hence, shocks can either propagate or dissipate, depending on the local structure. At the aggregate level, tipping points lead to non-linear regime changes in aggregate dynamics (Easley and Kleinberg, 2010). Thus, accounting for systems complexity and understanding network structures and propagation mechanisms is key to risk governance policy (OECD, 2011).

Therefore, the primary objective of this dissertation is to explore and evaluate different methodologies with particular advisory value for understanding and managing network effects against the backdrop of improving policy aimed at ensuring the stability and resilience of economic and financial systems. These methods are Agent-Based Models (ABM), Input-Output Analysis (IOA), and Vector Autoregressions (VAR). By employing these methods respectively in three distinct projects, this research aims to uncover their respective strengths, against the background of epistemological reflection, for managing network effects in economic systems. The concluding chapter of this dissertation will offer a comparative analysis of these methodologies to provide respective insights. Accordingly, this dissertation adds to the fragmented yet evolving literature on methodological contributions to risk governance and economic policy. OECD (2011) and the International Risk Governance Center (2018) describe the potential of ABMs and network analysis in the context of risk governance rather generally. Westerhoff (2008) and Westerhoff and Franke (2018) highlight the strength of ABMs for policy design and Bookstaber (2012) for understanding risks in the financial sector. In comparison, VARs are well established in financial risk management (see e.g., Zopounidis et al. (2021)), and economic (policy) analysis (see e.g., Kilian and Lütkepohl (2018)). However, to the best of my knowledge, there is no work explicitly relating the methods to the specific analytical steps of risk governance. While the supplementary material to the ISO 31000 Risk Governance Framework outlines techniques for specific steps (IEC/ISO, 2019), its guidance remains largely superficial. It does mention certain methods, however, it does not account for the types of models reviewed in this work. This dissertation aims to bridge this gap.

Although each project has its own topics and contribution, the contribution of this framework is that these three modeling approaches can be positioned as complementary tools with different potential to inform specific steps in risk governance, by having different strengths: ABM for exploratory modeling[3], IOA for locating structural dependencies and exposures, and VAR for quantifying past dynamic (causal) relations.

Thereby, this work contributes equally to two fields in the public sphere: economic policymaking and economic science. First, I support policymaking by demonstrating the specific strengths of various methodological approaches in relation to distinct stages of the risk governance process. In doing so, I aim to provide guidance to policymakers in identifying and engaging with

[3]This follows the conceptualization of exploratory modeling as discussed by Bankes (1993). Here, exploratory modeling is understood as a methodological framework that integrates parametric variation, sensitivity testing, scenario exploration, and even forecasting (possible future behavior under current trends and conditions).

suitable research expertise. Second, by systematically contrasting different approaches, I offer an overview that enhances mutual understanding among researchers, who are often highly specialized and may have limited insight into the merits of alternative methodologies. I provide guidance and support to early-career researchers aiming to address contemporary challenges in governing economic and financial risks. Additionally, I assist researchers in the field of complexity economics seeking funding by clearly articulating their work's relevance and methodological contributions to current societal and policy challenges.

In doing so, I directly support Sustainable Development Goal 8 (Decent Work and Economic Growth) and Goal 16 (Peace, Justice, and Strong Institutions), as I aim to strengthen institutions that foster economic development. Indirectly, this work also supports Goal 1 (No Poverty) and Goal 13 (Climate Action), as resilience-building is closely linked to climate adaptation and social protection efforts. Strengthened risk governance is essential to protect vulnerable populations from crisis events and to limit the spread and severity of poverty.


Source of pictures: Communications Materials by United Nations (2023).

## 1.2 Outline

The core of this dissertation comprises three projects, each employing approaches in complexity economics to understand or mitigate network effects. The first project focuses on agent-based modeling and analysis of a policy aimed at reducing deleveraging and herding spirals in financial markets. The second project involves simulating the propagation of price shocks using an Input-Output price multiplier model. Finally, the third project applies a Markov Switching Vector Autoregression to analyze the short-term effects of climate-related risks on inflation expectations and, in turn, the impact of both on different bond classes.

The selection of projects is based on a multitude of considerations. The methods are approaches widely used in the behavioral and complexity macroeconomics and finance community and fall within the expertise of the macroeconomic chairs supporting the Bamberg Research Training Group on Bounded Rationality, Heterogeneity, and Network Effects. In addition, I encountered the use of ABMs, IOA, and VAR at various conferences. Further, against the motivation to contribute to current topics, the projects address pressing issues that occurred directly before and during my research time. Thus, the ABM project assesses short-selling restrictions, a policy discussed in the aftermath of the COVID-19 market turmoil, and can tame downward market spirals. The IOA project puts the focus on cost-push inflation, which became an omnipresent issue due to Putin's invasion of Ukraine. Finally, the VAR project centers on the increasing concern among central bankers regarding the potential negative impacts of rising physical climate and green transition risks on price and financial stability. These climate-related risks are exacerbated by more frequent climate events and the EU's ongoing efforts to achieve net-zero emissions.

### 1.2.1 Paper 1

The first project is titled "Hush the Rush: Short-Selling Bans in Times of Stress". This study employs an agent-based financial market model, a computational approach that iterates agents' behavior in a generic financial market over discrete time steps. Unlike traditional models that rely on the assumption of a perfectly rational representative agent ensuring market equilibrium, ABMs embrace the complexity of the world and financial markets by utilizing heterogeneous, bounded-rational, interacting agents. This allows accounting for network effects and the modeling of market dynamics that deviate from equilibrium, offering a more nuanced understanding of market behavior under stress (Farmer and Geanakoplos, 2008).

In this vein, in the paper, a model is set up that accounts for the behavioral factors and network effects behind financial market crashes. This model, in turn, serves as a framework to evaluate the effectiveness of short-selling restrictions in mitigating price declines significantly below the fundamental value. The market model features heterogeneous traders switching between momentum-based and valuation-based strategies and a leveraged long-term investor. This de-

sign integrates key factors behind market crashes, such as herding, extrapolated behavior, and deleveraging. The strategy choices and orders rely on endogenous model variables observed by the agents. The interactions within the model lead to the emergence of different market regimes, effectively mimicking real financial market characteristics. In line with existing regulations, temporary short-selling restrictions are implemented after significant price declines.
The results demonstrate that short-selling restrictions hinder downward price discovery and lead to inflated prices. When analyzing the impact on prices above and below the predetermined fundamental value separately, the research reveals that although there is an increase in positive price distortion, the negative price distortion and severity of crashes are reduced. This implies that short-selling bans improve price efficiency and stability when prices are below their fundamental value. Additionally, the reduction in adverse network effects suggests that temporary short-selling bans bolster systemic stability.

### 1.2.2 Paper 2

The project is titled "Stress-testing Inflation Exposure: Systemically Significant Prices and Asymmetric Shock Propagation in the EU". It applies a shock propagation simulation exercise over the Input-Output tables from the World Input-Output Database. Input-Output tables provide information about the trade volume among all entities (eg, sectors), providing a real-world network structure (Miller and Blair, 2021).
Our research focuses on structural asymmetries in price shock exposures across the European Union, distinguishing between a selection of core and peripheral regions. Methodologically, it employs a Leontief price multiplier model to simulate cost-pushes to specific sectors. This can be thought of as stress-testing the impact of price shocks on consumer price indices (CPIs). To identify the sector prices that are especially significant, the shock responses from multiple analyses are compared. The study also distinguishes between direct and indirect inflation exposure across the EU core and periphery, accounting for both intra-regional effects and influences from non-EU countries. To derive further structural differences, the number of sectors required to impact the CPI significantly is compared and the cross-sectional ability to substitute price-inflated goods is estimated to gauge the dependencies. Ultimately, the diffusion curves of price

shocks in the most critical sectors are analyzed for both the core and the periphery regions. The results show that a small number of industries have a disproportionately large impact on consumer price inflation, with this concentration being more pronounced in the core regions than the periphery. The study also finds that peripheral EU countries are more exposed to inflation originating from non-EU countries and core EU countries, with a significantly greater impact on their CPI volatility than the core. Furthermore, our estimate of consumption substitution ability reveals that consumers in core countries can better adjust by substituting away from goods with rising prices. Overall, we show that consumers in EU peripheral countries are relatively more exposed to price volatility.

### 1.2.3 Paper 3

The paper's title is "Investigating the Impact of Climate-Related Risks: A Regime-Switching Analysis of Bond Market Dynamics and Inflation Expectations". The third approach employs a Bayesian Markov-switching VAR model in time series analysis. A VAR model captures the interdependencies among multiple economic variables, making it useful for understanding their relationships. The model accounts for different volatility regimes and shifts among them based on a Markov-switching mechanism. This approach is particularly advantageous because it allows for analyzing how interactions between economic variables vary across different volatility regimes within a single model (Krolzig, 1997).

The paper uses European data to explore different, closely related issues in the context of climate-related risks, prices and financial-market stability. First, it examines how green transition risk and physical climate risk affect market-based inflation expectations and various bond categories, including government, conventional corporate, and green corporate bonds, and their dynamic interactions. Second, it studies how shocks to inflation expectations influence bond markets, and third, how shocks to the different bond classes feed back into one another. The study uses news text-based green transition risk and physical climate risk indicators to measure the associated risks from an European Central Bank project.

We find that transition risk influences bond markets and short-term inflation expectations only during periods of low volatility. Moreover, we detect no significant divergence between conventional and green corporate bonds, suggesting that, so far, concerns about abrupt capital reallocations from the traditional to the green economy destabilising financial markets appear unwarranted. This, however, does not preclude the possibility of a future "too-late-too-sudden" transition scenario, while the evidence lends moderate support to concerns about emerging greenflation pressures. In addition, we find that physical climate risk has a stronger and more persistent negative influence on bond markets, particularly during periods of high volatility, with effects more pronounced for corporate than for sovereign bonds. Short-term inflation expectations are similarly affected, especially in the high-volatility regime, depicting a positive impact. Both results suggest that physical climate events cause supply disruptions that markets take notice of. Regarding the effects of both climate-related risks on long-term inflation expectations, we find no robust results, suggesting that expectations are well anchored in the long run. As climate-related pressures intensify, these relationships could likely shift, requiring careful attention in private and public risk governance.

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## Paper 1

# Hush the Rush: Short-Selling Bans in Times of Stress

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**Abstract**

Short-selling restrictions are often enacted during financial turmoil to promote market stability, though most research highlights their negative impact on market quality. This study examines the stability and effectiveness of these restrictions in preventing market crashes in an agent-based financial market model, where the fundamental value is controlled. The model features heterogeneous traders switching between momentum-based and valuation-based strategies and a leveraged long-term investor. This design incorporates herding, extrapolative behavior, and deleveraging—key drivers behind market crashes. The findings corroborate previous research, indicating that short-selling bans hinder downward price discovery and lead to inflated prices. By distinguishing the effects above and below the fundamental value, the study shows that while positive price distortion increases, negative price distortion and crash severity decrease. This suggests that short-selling restrictions enhance price efficiency and stability below the fundamental value. Furthermore, the mitigation of crash dynamics, along with the corresponding behavioral drivers and network effects, indicates that temporary short-selling bans contribute to systemic stability.

**Author's contribution**

I completed all components of this paper independently and in full as its sole author.

**Co-authors and affiliations**

Single-authored paper.

# 1 Introduction

Short-selling restrictions (SSR) are widely implemented during financial stress to maintain stability. Schinasi (2004) views price stability as crucial for the stability of the financial sector. For example, Adrian and Shin (2008) or Brunnermeier and Pedersen (2009) refer to asset market prices as the primary propagation channel during the Great Financial Crisis, as overlapping portfolios and falling prices led to deleveraging spirals. Despite SSR being imposed to promote stability, oddly enough, most SSR assessments focus on market liquidity and efficiency and find detrimental effects on both, which is strongly backed by theoretical elaborations.

However, research on the relationship between SSR and market or financial sector stability remains limited. This study seeks to address this gap by analyzing both efficiency and stability through an agent-based financial market model. The model incorporates the ability to control for fundamental value, thereby enabling a more comprehensive evaluation of SSR's effects.

Miller (1977) gives seminal theoretical reasoning for why SSR may distort the market price positively. His arguments are grounded in an efficient market for one asset with homogeneous agents and the idea that the price will eventually converge to its intrinsic value. Yet, traders do not know it and have heterogeneous expectations normally distributed around the fundamental value (F). With SSR, agents with negative information are excluded from trading, reducing supply and causing the price to rise above the F. Support for this so-called overvaluation hypothesis is provided by Harrison and Kreps (1978), Scheinkman and Xiong (2003) and Duffie et al. (2002). Diamond and Verrecchia (1987) attenuate it. They believe rational market participants would anticipate and correct inflated prices, so they argue that short-selling constraints only slow down price discovery.

Yet, recognizing regulators' intentions, Beber et al. (2020) suggest that research should give stability concerns more attention. It is axiomatic that price stability and efficiency are interrelated concepts. Price stability means prices remain within a benchmark range. The strong form of the Efficient Market Hypothesis by Fama (1970) claims markets fully incorporate all information. Fama (1991) develops his theory, adding that deviations from the efficient price occur due to market frictions. While the F is an almost philosophical concept, if one accepts it as a single price that reflects all available information and takes it as a stability benchmark, when a price is above its intrinsic value and falls, firstly, it can then be stated that efficiency and stability go hand in hand, and secondly, that downward frictions are not socially optimal.

However, it is known that agents are not rational and, due to behavioral factors, tend to extrapolate price movements. When scrutinizing human behavior, it is important to consider the motivations, abilities, and constraints.

The motivation of financial market participants is to maximize profits or minimize losses. Already Keynes (1936) linked greed and fear to market bubbles and crashes. Shiller (1987) survey results show that there are traders who only trade on price changes during crashes. In addition, Shiller (1981) shows that historical price trends can be disentangled from actual dividends. This extrapolate behavior is linked to herd behavior, where individuals imitate others. Market participants acting similarly create increased price pressure movements. Shiller and Pound (1989) see rational and non-rational causes for it. Bikhchandani and Sharma (2001) differentiate spurious herding, which is unintentional, similar behavior due to similar information, and intentional herding when investors choose to mimic others. The latter can especially be the case under uncertainty (Avery and Zemsky, 1998; Cipriani and Guarino, 2005).

The ability to realize desired orders depends on the resources at hand, like funds and assets, or the ability to borrow them. When investing with leverage, traders can place higher order sizes. At the same time, security borrowing allows them to short-sell assets they do not own. Geraci et al. (2018) uncover that short-sellers are particularly active on days with extremely high price drops. In this context, it is worth highlighting that short-selling can also be used as a technique for manipulative or predatory purposes. Bernheim and Schneider (1935) describe bear raids, where a group of investors collaborates to heavily sell a security, creating a strong negative price signal and potentially inciting panic to drive down its price. Another manipulative strategy is called short-and-distort, here traders short-sell a security and then artificially spread false or misleading information to drive down its stock price (Goldstein and Guembel, 2008; Mitts, 2020). Brunnermeier and Pedersen (2005) and Brunnermeier and Oehmke (2014) describe predatory short-selling, where sellers aggressively short-sell to harm a financially weak business, further driving down its stock price as its equity erodes. Next to short-selling, another ability-enhancing aspect is leverage, as it allows investors to amplify their purchasing power and can inflate prices. In turn, higher prices translate to more equity and more buying power (e.g. Geanakoplos (2010)).

The constraints of financial market players result from the fact that no one can bear infinite losses and alike endless risk. Thus, traders are restricted by legislation or risk management rules limiting their conduct. While leveraged traders experience more and more freedom during bull markets, during bear markets, the walls are closing in. Then leverage contributes to extreme price declines because it forces market participants to sell assets once markets turn down. When leveraged mark-to-market portfolios experience losses due to price declines, a deleveraging feedback loop can start (also termed fire sales). This is because, on the one hand, higher negative returns increase risk measures and thus prudent equity requirements; on the other hand, equity erodes when prices fall, which both causes selling pressure and again pushes prices further down (Brunnermeier and Pedersen, 2009; Adrian and Shin, 2008).

Keeping these behavioral factors in mind, a corrective downward price movement is likely to be prolonged below the F. If this is the case, efficiency and stability are both harmed and hence, downward frictions would be socially optimal to protect both. This being said, Hong and Stein (2003) state concerns about SSR, as they omit negative information from being factored into stock prices. This can amplify the formation of bubbles during bans and cause prices to drop more after bans end. So, they are concerned about a higher risk of market crashes due to SSR.

Against this background, this work aims to explore the mechanism of SSR and how they affect market dynamics, systematically addressing several key questions. First and foremost, how effective are SSR in reducing price drops far below the F? Second, are SSR an effective tool to contain behavioral spirals such as herding to extrapolate behavior and deleveraging? Third, to what extent are the concerns that a) SSR harm efficiency and b) promote the build-up of bubbles that burst when the ban is repealed, justified? Fourthly, how quickly should SSR ideally be deployed and removed?

The first question relates to market stability. The second question aims to evaluate the systemic stability significance of SSR, capturing the effect on network effects. The first question addresses concerns about stability and efficiency issues, and the second question pertains to the optimal use of SSR.[1] To address these questions, this work employs a robust analytical framework, incorporating rigorous variable selection and building on various research approaches, including empirical, experimental, and computational works.

Empirical research on SSR's effects is diverse, employing varying approaches and findings, with market quality measures, commonly in terms of liquidity or efficiency, being the primary focus. Stability, however, remains a somewhat marginalized concern. Yet, since stability and efficiency are strongly interconnected concepts, many indicators used to examine efficiency aspects also hold significant value when viewed through the lens of stability. These range from analysis of returns to market distortions and shifts. In the context of return analyses, valuable metrics are the skewness and the appearance of excess negative returns (Chang et al., 2007; Bris et al., 2007). The latter is typically defined as daily returns below two return standard deviations of a reference period. In addition, several methods have been established in the literature to examine how SSR affect asset performances subject to restrictions, comparing them with themselves in times in which they were not restricted or with other non-restricted assets in a common market at the same time. The basic idea behind these comparisons is to uncover frictions to the news incorporation process in return behavior by abnormal returns of individual assets to a reference market. Popular approaches are to compute the abnormal returns,[2] or the upside and downside cross-auto-correlations between individual stock returns and markets, to gauge friction by differences in the realization of beta factors (Bris et al., 2007; Boehmer et al., 2013; Beber and Pagano, 2013). While the results are somewhat heterogeneous, there is a discernible tendency towards the identification of positive distortion.

Hauser and Huber (2012) attribute this variability in findings to the likely inability to account for F using empirical methods. Thus, approaches that allow for controlled environments, such as experiments, are particularly meritorious. Grounded on the seminal financial market exper-

[1] Notably, the project is only concerned with the temporary use of SSR in times of stress, when agents tend to deviate most from rational behavior. The importance of short sales as elements of multiple financial instruments is indispensable, see e.g. Kosowski and Neftci (2014).

[2] See Bris et al. (2007), Chang et al. (2007), Boulton and Braga-Alves (2010), Harris et al. (2013), Beber and Pagano (2013), Bessler and Vendrasco (2022) and Spolaore and Le Moign (2023)

imental laboratory setup by Smith et al. (1988) with human participants, Ackert et al. (2005), Haruvy and Noussair (2006) and King et al. (1993) experimentally examine price effects of short-selling restraints. All authors obtain results depicting positive price distortions in the absence of the traders' ability to short-sell.

Further computational models have been utilized as a laboratory framework to explore SSR. This approach is particularly suitable for investigating the ability of SSR to contain market crashes. Farmer and Geanakoplos (2009) stress agent-based models are valuable for accurately modeling market behavior during stress and uncertainty. They feature individual agents with their own behavioral rules that allow them to account for bounded rationality and network effects. The collective system behavior emerges from the actions of agents, which are shaped by their interactions and environmental changes. Thus, this methodology enables the simulation of non-equilibrium phenomena, such as market crashes. Westerhoff (2008) picks up on the upsides of agent-based modeling, pointing out further advantages. He emphasizes the advantages of testing regulatory policies in financial markets. The benefits in this realm are numerous. It is noteworthy that the intrinsic value can be kept constant. In addition, agent-based financial models can mimic the price pattern of usual market behavior and unusual events in a controlled environment. This allows for generating as much data as required to examine policy effects thoroughly. In particular, this can be very useful in assessing the impact of regulatory means in rare situations such as market crashes. In addition, tracking all relevant variables and adjusting the policy parameters is possible. Hence, researchers can test the effect of policy parameters for different magnitudes and foster an understanding of the functioning and effects of the regulatory mechanism.

A series of scholars have conducted their analytical and numerical studies on agent-based finance models grounded on the seminal adaptive belief system model with fundamental and technical trading by Brock and Hommes (1998). Anufriev and Tuinstra (2013) examine short-selling impediments in the form of short-selling costs. The findings indicate that short-selling restrictions lead to price inflation and increased market volatility. Yet, under specific circumstances, it can also be seen that distortion below F is reduced. Furthermore, in 't Veld (2016) analyzes additional costs for short-selling and leverage, thereby restricting excessive selling and purchasing positions. To this end, he prepares two setups, one with fundamental and technical trading behavior in co-evolution and one with fixed weights of fundamentalists, optimists, and pessimists. His findings are distinct. First, mispricing and price volatility increase as the fundamental strategy is inhibited. Secondly, restrictions reduce volatility, but price distortion remains elevated. Dercole and Radi (2020) study the effectiveness of the uptick rule, a specific type of short-sale restriction that only allows short sales after a price increase. Notably, they base their assessment on regulators' goals to reduce price falls far below F and find that crash frequency as well as severity are mitigated. However, they anticipate criticism of their model for being overly deterministic and suggest that a stochastic model, which incorporates diverse trading strategies and emotions, would provide a more comprehensive framework.

Following up on this, the chosen setup does not only have stochastic components but also carefully incorporates the crucial behavioral drivers behind market crashes. The base model uses building blocks of Franke and Westerhoff (2012) and is further extended in the fashion of Schmitt and Westerhoff (2017) with a layer of individual agents. They all have their own asset stocks and individual trading orders guided by heuristic rules that are grounded on the key ideas of fundamental and chart analysis. In each period, traders reevaluate which strategy they want to follow based on recent profits, considerations of market circumstances, and other traders' behavior, making them prone to herd behavior. In addition, following the design of Aymanns and Farmer (2015), one long-term investor is added. It only risk-adjusts its position based on a RiskMetrics Value at Risk model that captures the key principles of risk management for leveraged traders. This extension adds the pro-cyclical component of leverage to the model, which is also behind fire sale dynamics. Building upon this, the emerging price evolution replicates characteristics of real financial market dynamics as a fat-tailed distribution of returns, volatility clustering, absence of autocorrelation, a long memory effect in daily returns, and bubble and crash price patterns. For the analysis, SSR is implemented temporarily, in line with current regulatory frameworks, when the price significantly plummets. The dynamics under SSR are then compared to simulations without SSR, specifically to samples where a hypothetical ban is imposed according to the enactment rules.

In general, the findings of previous works can be confirmed. In concrete terms, this means that prices are inflated when SSR are introduced, as downward price discovery is inhibited. Yet, given the stability focus of this work, this also means that SSR are shown to be effective in reducing downward market distortions and, thus, the severity of crashes. Likewise, SSR are shown to effectively mitigate behavioral network effects that exacerbate price declines, including herding and deleveraging. Since these factors fuel the propagation of shocks across markets, it can also be deduced that SSR can contribute to the containment of systemic risk. Moreover, the widespread concerns regarding SSR can be partly alleviated, since there are no price crashes when bans are lifted. In addition, as downward price movements are found to be impeded, it can be seen that above the F price efficiency is reduced and SSR lead to price bubbles. Yet, as SSR support corrective movement below the F, they also support price efficiency in this area. This supportive effect below the F is found to be stronger than the bubble effects above it and thus this work uniquely contributes that SSR can represent a net benefit gain in times of stress.

# 2 Methodology

In this section, the model structure is first presented. Next, the parameter settings and the model's validation are detailed. Finally, the dynamics of the model are discussed, with a focus on elucidating the underlying mechanisms that drive the model's behavior.

## 2.1 Base Model

The model's main skeleton is assembled using building blocks of Franke and Westerhoff (2012). Minor changes are made to the original time structure, and the here presented model is based on nominal prices instead of logarithmic prices. Additionally, the model's cornerstones are extended in two ways. The first extension is a layer with individual traders, following Schmitt and Westerhoff (2017). This enables the integration of individual trading and individual asset stocks, which is necessary for effective policy implementation. As a second extension, a representative leveraged long-term investor named ”bank” is introduced in the fashion of Aymanns and Farmer (2015), which only adjusts its position to match the leverage rate to the market risk.

This introduces the leverage factor as a driving force behind market dynamics.

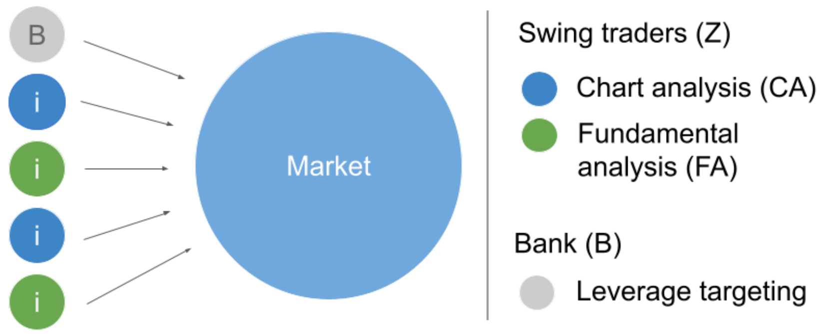



Figure 1: This model overview illustrates the market structure. The market is provided by the market maker. All one hundred market participants are given by N = {B, Z}. B is one representative leveraged long-term investor. The remaining ninety-nine are swing traders given by $Z = \{i_1, i_2, \ldots, i_{99}\}$. For reasons of space, these are shown in reduced numbers. It should also be noted that they are constantly adapting their strategy (chart analysis or fundamental analysis) and that the strategy distribution depicted here is only exemplary. Against this background, the price evolution results from extrapolating, mean-reverting, and leverage-adjusting trades.

#### 2.1.1 Market mechanism

The model's heart is the price adjustment function. The price of the asset is based on the previous price, $P_{t-1}$, and adjusts according to aggregate excess demand, $AD_t$, scaled by parameter $\alpha$. Following Day and Huang (1990), the market maker equation is:

$$P_t = P_{t-1} + \alpha AD_t \tag{1}$$

Intuitively, aggregate excess demand is calculated as the sum of all individual trading orders. This is the demand of the bank, $D_t^B$, and all swing traders, $D_t^i$. The equation for the aggregate demand is:

$$AD_t = D_t^B + \sum_{i \in Z} D_t^i \tag{2}$$

#### 2.1.2 Short to medium-term speculators

In each simulation step, swing trader $i$ reconsiders buying or selling based on the trade order, $TR_t^{S,i}$, derived from one of the strategies, $S = \{CA, FA\}$, fundamental analysis ($FA$), or chart analysis ($CA$). The model generates hypothetical trading orders for both strategies. Which one realizes is determined by an indicator function, $I_t^i$, showing the strategy decision in the demand function, $D_t^i$. This is given by:

$$D_t^i = \begin{cases} TR_t^{FA,i} & \text{if } I_t^i = FA \\ TR_t^{CA,i} & \text{if } I_t^i = CA \end{cases} \tag{3}$$

Prior to examining the selection process, the strategies are briefly introduced. The fundamental strategy is based on the idea that the price will eventually converge to its F.

$$TR_t^{FA,i} = \beta_{FA}(F - P_{t-1}) + \varepsilon_t^{FA,i} \tag{4}$$

The chart analysis trading signal is grounded on the belief in a continuation of the current price trend.

$$TR_t^{CA,i} = \beta_{CA}(P_{t-1} - P_{t-2}) + \varepsilon_t^{CA,i} \tag{5}$$

Where $\beta_S$ are reaction parameters, $F$ is the fundamental value, and $\varepsilon_t^{S,i}$ are noise terms. The conceptualization of the noise terms is inspired by Schmitt and Westerhoff (2017), who assume a correlation between the noise terms. Following this, the noise term comprises both a macro and an individual component. The macro component can be understood as misinformation, disinformation, or spurious herding. The individual component accounts for bounded rationality and, in the case of chart analysis, also for various trading rules that fall under this umbrella term. $\chi_t^S \sim \mathcal{N}(0, \sigma_S)$ represents the cross-trader i.i.d noise term, and $\chi_t^{S,i} \sim \mathcal{N}(0, \sigma_S)$ is the individual i.i.d noise term.

$$\varepsilon_t^{S,i} = (1 - h)\chi_t^{S,i} + (h)\chi_t^S \tag{6}$$

Subsequently, the approach for selecting the mentioned strategies is presented. Boiled down, traders evaluate the so-called fitness of the strategies to determine the choice probabilities with which the decision is made. The fitness measures, $U_t^{S,i}$, are specified as:

$$U_t^{CA,i} = c_G G_t^{CA,i} + c_H H_t^{CA}; \tag{7}$$

$$U_t^{FA,i} = c_G G_t^{FA,i} + c_H H_t^{FA} + c_M M_t; \tag{8}$$

These fitness functions comprise several components: a herding effect, $H_t^S$, a misalignment effect, $M_t$, and hypothetical trade gains, $G_t^{S,i}$. Correspondingly, the parameter, $c_H$, denotes the herding effect strength, $c_M$, captures the impact of misalignment, and $c_G$, determines the influence of hypothetical trade gains.

$$G_t^{S,i} = \mu \cdot G_{t-1}^{S,i} + (1-\mu) \cdot (P_{t-1} - P_{t-2}) \cdot TR_{t-2}^{S,i} \tag{9}$$

$G_t^{S,i}$ is the profit memory function for trader, $i$, of strategy, $S$, at time, $t$. Since traders want to maximize their profits, they prefer using the trading strategy that recently gave them the highest hypothetical gains. In this vein, the equation represents a weighted average of hypothetical profits, preferentially taking into account short-term past profits. The first term, $\mu \cdot G_{t-1}^{S,i}$, represents the share of the previous profits' value, determined by the weight parameter, $\mu$. The second term, weighted with $(1-\mu)$, represents the most recent observable hypothetical profit. To compute this, the agents consider the hypothetical trade orders of both strategies two periods ago, $TR_{t-2}^{S,i}$, regardless of execution. The orders are served at the end of the same period in which they enter the market at $P_{t-2}$. As traders are only able to observe the price change to $P_{t-1}$ in $t$, they only then recognize whether they made profits or losses.

As already elaborated, herding behavior is a well-observed phenomenon in financial markets. This is implemented in the model by assuming traders know how the other traders have traded in the last period. The corresponding value of the term is determined using a program code. A function counts the number of times the strategy symbol appears in the array from the previous period. To compare the strategies directly, the relative share is calculated by dividing by the number of swing traders.

$$H_t^S = \frac{\sum_{i \in Z} 1(I_{t-1}^i = S)}{|Z|} \tag{10}$$

Furthermore, agents consider the absolute misalignment between the last observable price and the fundamental value. The intention behind this term is that once traders perceive the distortion to be unreasonably high, they expect a correction. To keep the exponential nature of the relation that is assumed by Franke and Westerhoff (2012), who use log prices, a transformation parameter, $\tau_{\text{exp}}$, is added.[3]

$$M_t = (\tau_{\text{exp}}(F - P_{t-1}))^2 \tag{11}$$

Since the relative difference in fitness is the pertinent factor, computing the disparity between the two equations simplifies the model.

$$U_t^i = U_t^{FA,i} - U_t^{CA,i} = c_G(G_t^{FA,i} - G_t^{CA,i}) + c_H(H_t^{FA} - H_t^{CA}) + (c_M M_t) \tag{12}$$

Given the fitness considerations, the likelihood that a strategy is chosen is determined by the choice probability function, $\Pi_t^i$, following Brock and Hommes (1998).

$$\Pi_t^i = \frac{1}{1 + \exp[\delta U_t^i]} \tag{13}$$

$\delta$ represents a choice intensity parameter. In the next step, a program function draws one strategy with the given probabilities and returns the corresponding strategy symbol. Here, this is illustrated with the indicator function, ($I_t^i$):

$$I_t^i = \begin{cases} FA & \text{with Prob } \Pi_t^{FA,i} \\ CA & \text{with Prob } \Pi_t^{CA,i} \end{cases} \tag{14}$$

#### 2.1.3 Long term investor

To add a pro-cyclical leverage component to the model, similar to Aymanns and Farmer (2015), one so-called bank, $B$, is introduced, which can be understood as a representative long-term investor that only adjusts the size of its total positions according to the perceived risk measure by a scaled RiskMetrics Value at Risk model, $VaR_t$.

[3]This transformation is necessary, as in the original set-up the fundamental value is zero, and $P$ can become negative. Yet, this would render the subsequent introduction of a long-term trader unfeasible, as this trader always operates based on maintaining a positive portfolio value.

$$VaR_t = 2,33(\frac{1}{L}\sum_{t-L}^{t}(r_{1,t} - \bar{r})^2) \tag{15}$$

The term in parentheses after the Z-score $2.33$ is a volatility estimate. $r_{1,t}$ is the return of one day. Returns are computed as percentage changes from $P_{t-2}$ to $P_{t-1}$. $\bar{r}$ is the mean of all returns, and by assumption 0. $L$ is the look-back period, which determines how far into the past returns are considered. The Z-score, in turn, adjusts the volatility estimate to correspond to a 99 percent confidence level in a standard normal distribution, ensuring that the calculated loss estimate is not exceeded with a probability of 1 percent. Based on this VaR, the bank determines its target leverage rate.

$$LR_t^{Tar} = \Psi VaR_t \tag{16}$$

In this equation, $\Psi$ represents an additional scaling parameter to put the leverage target at a reasonable height, following Aymanns and Farmer (2015) closely. $LR_t^{Tar}$ is updated at the beginning of every period in reaction to the new price that is determined at the end of the last period, which directly affects the bank's equity.

For the leverage adjustment trading rule, a model-compatible approach is designed. To this end, the bank obtains an account, tracking among others, the equity, $E$, and debt, $DB$, amounts. Appendix A details the bank's account structure, the derivation of the trading rule, $D_t^B$, and economic interpretation.

$$D_t^B = \frac{LR_t^{Tar}E_{t-1} - DB_{t-1}}{P_{t-1}} \tag{17}$$

### 2.1.4 Model validation

Model validation is essential in ensuring the accuracy and reliability of simulation results. It involves comparing the simulation results with statistics of real-world data to determine the degree of agreement between them. The forthcoming simulation dynamics are based on the parameter setting presented in Table 1. Day-to-day financial market statistics possess a multitude of stylized facts. The model has been carefully calibrated to replicate the most prominent statistics of real financial market dynamics and thus is understood to present a sound framework for policy experiments. To the end of validation, it is focused on aspects of return behavior such as fat tails, volatility clustering, absence of autocorrelation, and long memory returns.

Further, in Figure 2 the model output is presented, demonstrating that it is able to replicate these stylized facts. The corresponding simulation run is based on 5,000 observations, and a transient period of 1,000 periods has been erased. The fundamental value has been set to 1. As the model is calibrated to replicate daily data, the output corresponds to a time horizon of roughly 20 years.

Prices in financial markets do not always reflect their fundamental value. In fact, regular periods of pronounced divergence emerge in the form of bubbles and crashes. In significant parts, these dynamics are market-endogenous, as backed by numerous laboratory experiments. For comprehensive overviews, see Palan (2013) or Porter and Smith (2003). The first panel displays the model's price evolution. The model generates a bubble and crash pattern and lasting phases of under- and overvaluation of over 30 percent.

The second panel presents the relative daily price changes (returns). Note that as the fundamentals are held constant. Nevertheless, there are excessively high price movements, reaching as much as over 10 percent.

Although the return distribution in financial markets is bell-shaped like a normal distribution, it differs in a particular way. This phenomenon, commonly described as fat tails, refers to a distribution that shows more probability mass in the center and its tails. From the histogram in the center, it is clear that this is the case in the model. To obtain a better impression of the tails, the hill index is computed. Its calculated value is 3.39, suggesting an accurate approximation of actual financial data.

Financial markets' price paths are close to a random walk, or put differently, price movements are uncorrelated. The autocorrelation function of raw returns is depicted in the second plot from the bottom up. Since, for almost all lags, the values are within the 95 percent confidence bands, the autocorrelation of the raw returns is not significant. Therefore, the price evolution is random and entirely unpredictable.

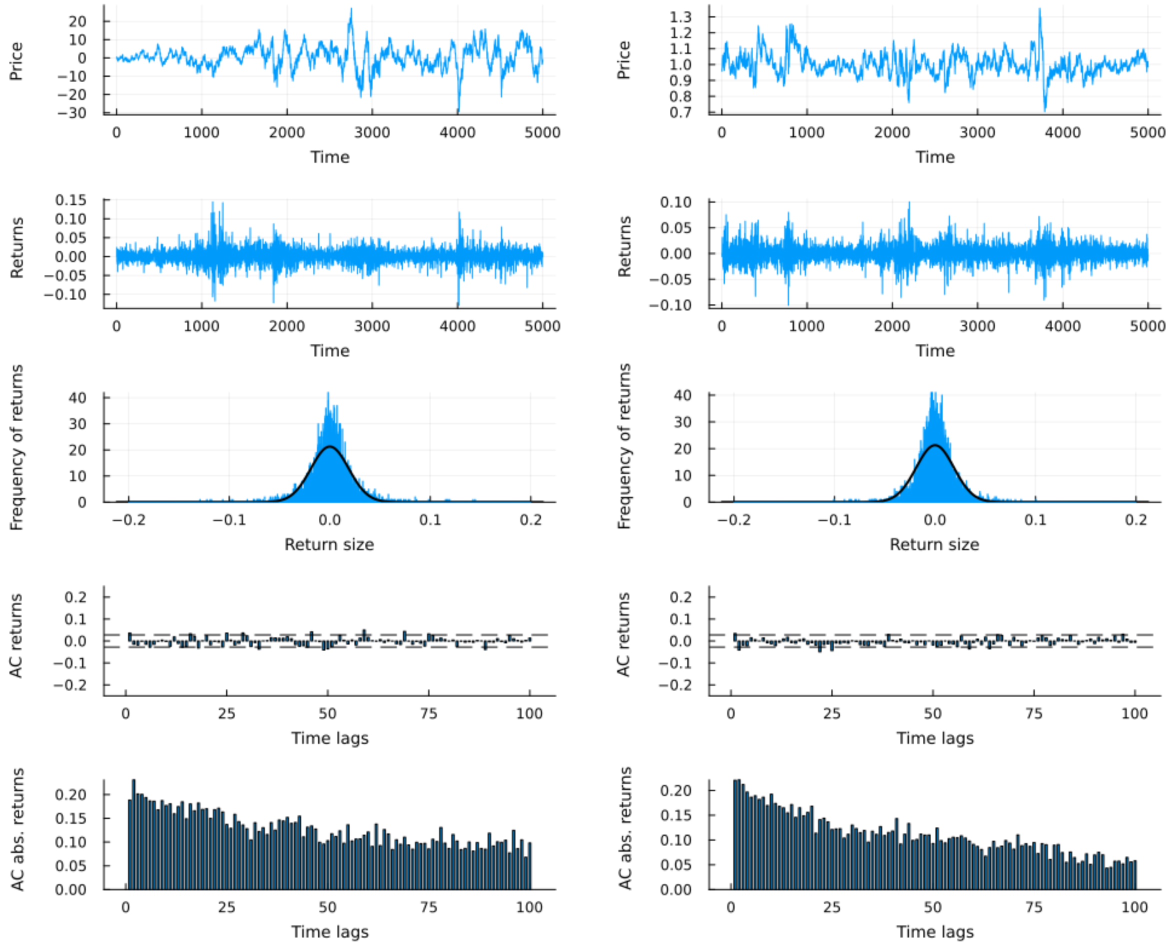



Figure 2: Stylized facts: The graph illustrates a comparison between the observed patterns in financial market data of BMW shares (on the left) and a representative simulation run generated by the model (on the right). The actual data is sourced from LSEG/Refinitiv, encompassing 5000 periods spanning from December 1, 2004, to January 30, 2024. To enhance comparability between the upper two price series plots, the price movements were detrended using the 200-day moving average as an approximation for the fundamental price.

Table 1: Parameter Settings

| **Parameter** | **Value** | **Parameter** | **Value** | **Parameter** | **Value** |
|---|---|---|---|---|---|
| $\alpha$ | 0.0005 | $\tau_{\text{exp}}$ | 20 | $L$ | 200 |
| $\beta_F$ | 1 | $c_M$ | 0.05 | $\Psi$ | 4.5 |
| $\beta_C$ | 1 | $c_H$ | 10 | $F$ | 1 |
| $\sigma_F$ | 0.25 | $c_G$ | 650 | $AS_1^i$ | 20 |
| $\sigma_C$ | 1.75 | $\delta$ | 1.67 | $AS_1^B$ | 300 |
| $h$ | 0.5 | $\mu$ | 0.99 | $DB_1^B$ | 150 |

Despite this unpredictability, in real markets, it can be observed that minor price movements are more likely to be followed by minor price movements and vice versa. This is known as the long-memory effect. Price dynamics exhibit episodes of low volatility and episodes of high volatility. Therefore, clusters of distinct volatility emerge. This phenomenon is already apparent from the top of the second graph. Additionally, the auto-correlation function for absolute returns over a hundred lags is displayed in the bottom panels for sound evidence. It is positive and shows a steadily declining form. Volatility levels seem to persist and vanish, demonstrating long memory and volatility clustering.

### 2.1.5 Discussion of model design and dynamics

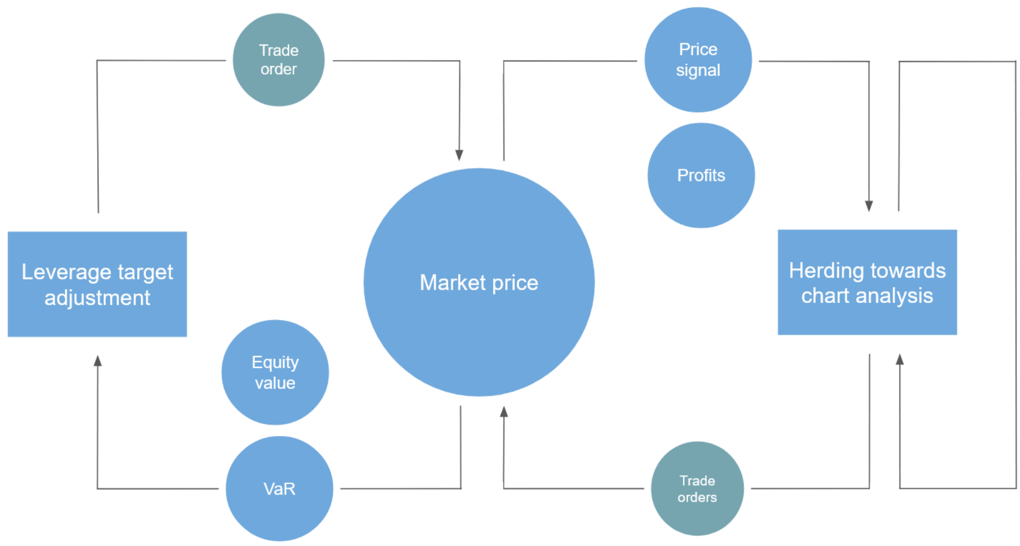



Figure 3: The propagation effects and how they reinforce themselves and each other, as specified in the model. On the right-hand side (RHS), "herding" and "extrapolate behavior" are merged into a single aspect, "herding towards chart analysis". On the left-hand side (LHS), there is a leverage adjustment. The two factors are linked via the market price.

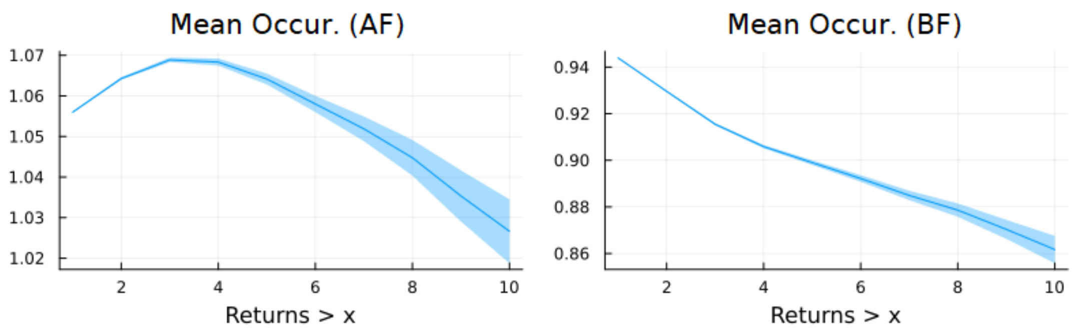
Subsequently, the model dynamics will be discussed to provide an understanding of the underlying behavior. Initially, it is important to note that given the demonstrated random walk nature of price dynamics, the noise terms hold significant relevance. Of course, these do not explain the replication of the other characteristics. Yet this will be done now, by linking the movements of the price evolution to the underlying metrics and laws of motion in the model setup. The behavioral factors that drive crash dynamics in reality have already been elaborated.

For the replication of the model, the strategy decision of every trader in each period plays a key role. Different strategy distributions result in varying volatility levels and market drifts. As previously elaborated, for the strategy choices, the outputs of individual fitness functions are compared. Its components change in size, allowing the agents to adjust their behavior to the current market situation. The pro-cyclical leverage component in the model additionally promotes these dynamics.

To illustrate how market trends and, consequently, crashes (or bubbles) emerge in the model, an exemplary narrative is presented, supported by Figure 3, which illustrates all the influence channels in the model. As a starting point, we envision a scenario in which chartists hold a larger market share and go short. Due to their dominance, the price goes down. In the next period at the RHS, several factors will need to be considered. The price drop strengthens the trading signal and increases the probability of a stronger sell-off. In addition, the market dominance of the bearish chartists has an informational spillover. Hence, due to herding considerations, the attractiveness of the chartist rule makes it more likely that more agents will choose to extrapolate the price movement with a stronger signal in the next period. At the LHS, at the same time, when the price goes down, this has two effects on the bank's position. First, all price changes affect the market risk measure. Thus, when a comparatively high negative price change occurs and significantly affects this measure, the bank would have to risk-adjust its position and sell assets. Second, the bank's equity decreases whenever the price decreases. Consequently, it has to sell assets to meet its leverage target again. This additional selling pressure, in turn, strengthens the negative price signal in the chartist trading rule. In the next time step at the RHS, the fitness function of the chartist rule is elevated by the agents realizing (hypothetical) profits. Accordingly, the spirals reinforce themselves and one another. While this exemplary story provides a good understanding of the underlying laws of motion and how market trends arise, the realization of the noise term can weaken or reverse a trend, depending on its size. However, when the market is in a regime where chart analysis is the prevailing strategy and the bank's risk measure is increased, the trade orders entering the market are, in general, higher. This increases the likelihood of trend fostering and higher market distortions.

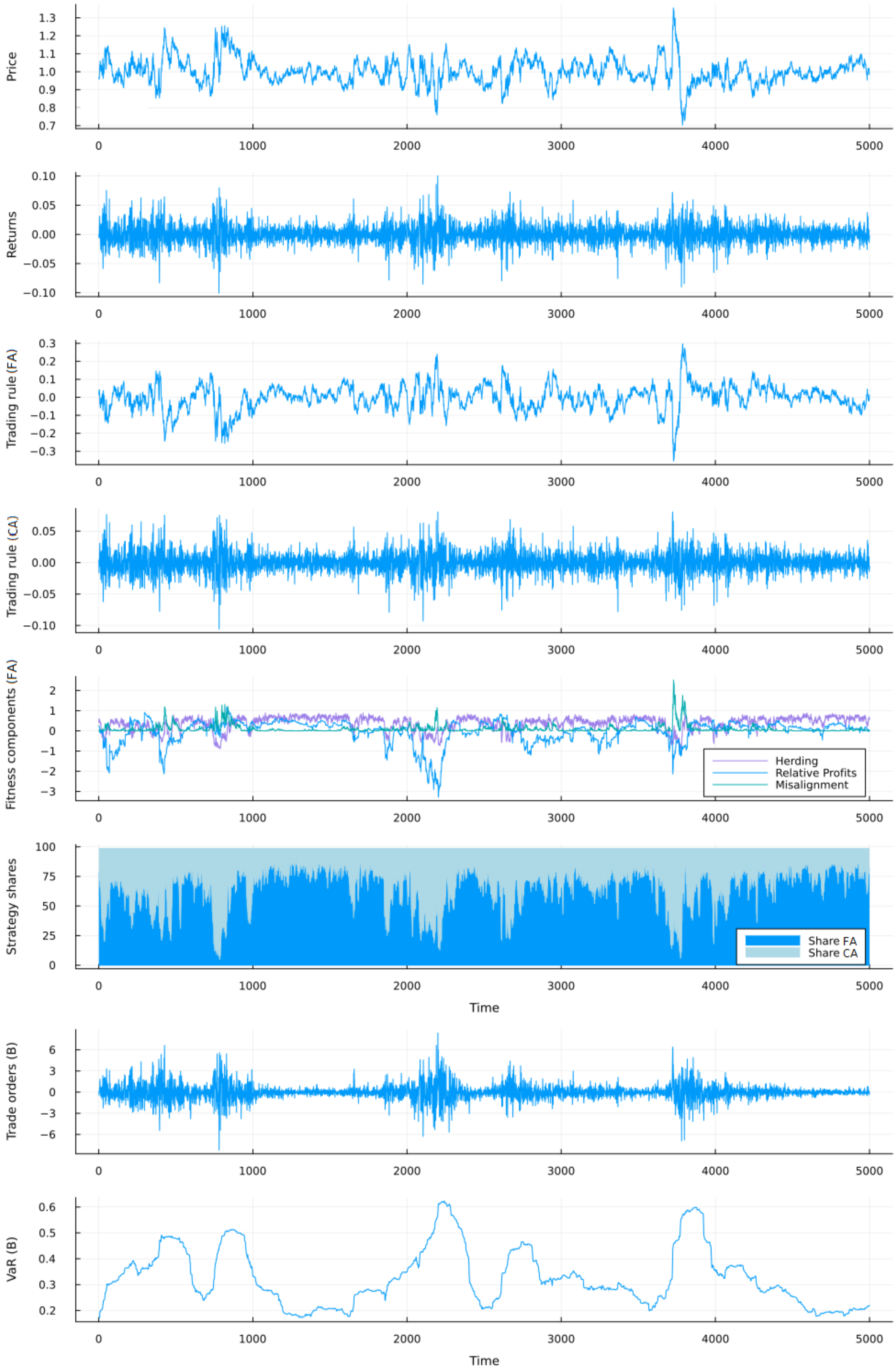
Figure 4 illustrates the power of the described mechanisms by showing the bias in the occurrence of negative returns of different sizes. Specifically, the mean prices at which different sizes of negative market returns occur in 1000 simulation runs are plotted for the case above F (AF) and below F (BF). The curves both show an initial bow, indicating that smaller returns occur more frequently, closer to F, which can be attributed to the distinct regimes and volatility clusters. Much more interesting, however, after the bows, in both cases, the mean occurrence price of negative returns exhibits a stronger negative bias, the stronger the negative returns are, demonstrating the importance of the downward spirals in the model dynamics.

Figure 4: Mean occurrence prices of negative returns by size




To further deepen the comprehension of the model, Figure 5 displays market and trading behaviors as well as underlying pertinent metrics. Panels 1 and 2 show the price and return evolution of Figure 2. The corresponding behavior of swing traders is depicted in panels 3 through 6, while the bank's activities are shown in panels 7 and 8. A detailed examination of the juxtaposition of metrics allows for an understanding of co-dynamics. For example, it can be seen how the crash (/bubble) formations (e.g., around periods 2200 and 3800) coincide with more intensive trading activity of chartists and the bank. For the chart analysis, the trading order size and the market share rise, alongside the relative hypothetical profits and the herding term turning in favor of the chart analysis. Additionally, the bank's VaR/leverage target and leverage adjustment orders are demonstrated to be simultaneously amplified during these phases. Furthermore, it is evident that during periods of pronounced market distortion, the misalignment term experiences a sharp increase. Consequently, numerous swing traders anticipate a price reversion, pivot toward fundamental analysis, and promote a market correction.

Figure 5: Functioning of the model



# 3 Analysis

The following section scrutinizes the effects of SSR. In the first step, the experimental setup is presented, showcasing how the policy mechanism is implemented. In the second step, the observatory variables are introduced, and their results are laid out.

## 3.1 Experimental setup

To evaluate the policy effects, the model is run without and with SSR in place in series. To have a significant number of observations, the model is simulated for 5000 periods, repetitively 5000 times, for both scenarios. To have appropriate comparison data, it is only looked at times when the restrictions bind, and respectively at phases in which the policy would have been hypothetically in force. To address the concerns raised by Hong and Stein (2003), which suggest that bubbles emerge and burst after restrictions are lifted, the two trading weeks following the ban periods are also tracked.

The enactment of SSR is exercised in line with the EU regulation 236/2012, giving regulators the power to set SSR in place in case of ”exceptional circumstances” or a ”significant fall in the price”. Based on this, SSR are implemented if the price drops by more than the policy threshold $\theta$ in one period.[4] For the initial analysis, $\theta$ is set to -5 percent but is later varied to test the robustness of the results for different values. The ban is technically implemented by setting the ban parameter $\rho$ for 20 periods from ”inactive” to ”active” after the threshold is exceeded. This policy length is only an initial value, and the effects are subsequently tested for their sensitivity to changes in this parameter, $\Lambda$. 20 periods are used as this number corresponds to one month in trading days. This is the ban length most EU countries chose at the start of the COVID-19 pandemic, for an overview see Bessler and Vendrasco (2021).

Transitioning to the technical implementation in the model, let’s recall that in its simple form, short-selling is a trading strategy in which an investor sells a borrowed security with the expectation that its price will fall and repurchase it later. To temporarily prohibit this practice in the

[4]Policy phases that would extend beyond the end of the simulation run and are artificially shortened by this are not taken into account, as the length varies and this could result in distorted values. The policy mechanism is deactivated in the transient phase.

model, traders' sale orders are limited to the number of shares they hold. This is accomplished in two steps. First, asset stocks, $AS_t^i$, in the form of equation (18) are introduced for all traders. The two cases in the equation refer to policy inactivity and activity. For SSR to be in place, the added maximum function ensures that the asset stock will not be negative. Economically, this means that agents can no longer engage in security lending.

$$AS_t^i = \begin{cases} AS_{t-1}^i + D_t^i & \text{if } \rho = \text{inactive,} \\ \max\{AS_{t-1}^i + D_t^i, 0\} & \text{if } \rho = \text{active.} \end{cases} \tag{18}$$

Second, trade order sizes are limited on the downside to the amount $AS_t^i$. To this end, equations (4) and (5) are substituted by (19) and (20). Hence, swing traders can only sell assets that they have in their portfolio and can not short-sell anymore.

$$TR_t^{F,i} = \begin{cases} \beta^F(F - P_{t-1}) + \varepsilon_t^{F,i} & \text{if } \rho = \text{inactive,} \\ \max\{\beta^F(F - P_{t-1}) + \varepsilon_t^{F,i}, -AS_{t-1}^i\} & \text{if } \rho = \text{active.} \end{cases} \tag{19}$$

$$TR_t^{C,i} = \begin{cases} \beta^C(P_{t-1} - P_{t-2}) + \varepsilon_t^{C,i} & \text{if } \rho = \text{inactive,} \\ \max\{\beta^C(P_{t-1} - P_{t-2}) + \varepsilon_t^{C,i}, -AS_{t-1}^i\} & \text{if } \rho = \text{active.} \end{cases} \tag{20}$$

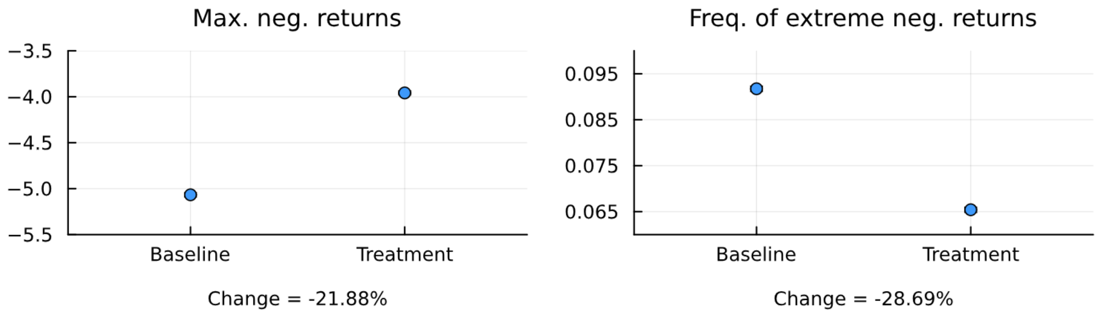
## 3.2 Metrics and results

The analysis centers on the impact of SSR on the effectiveness of containing crashes (far) below the fundamental value and the underlying behavioral factors. Additionally, a comprehensive investigation of common concerns is conducted, covering efficiency losses and post-restriction crashes. Ultimately, with the objective of improving the understanding of the optimal design and utilization of SSR, its impact is tested for different policy parameters. All estimates are provided as means of the simulation runs with 95 percent confidence bands. However, to improve readability, only the variable names will be used subsequently when referring to metrics. Further details on the variable design are laid out in Appendix C.

### 3.2.1 Analysis of Crash Prevention

To quantify the effect of SSR on crash formations, a set of metrics is considered. These cover the maximum negative returns, the frequency of extreme returns, trade order interactions to gauge the impact on the underlying behavioral drivers, and the negative price distortion to measure the severity of crashes far below the fundamental value.

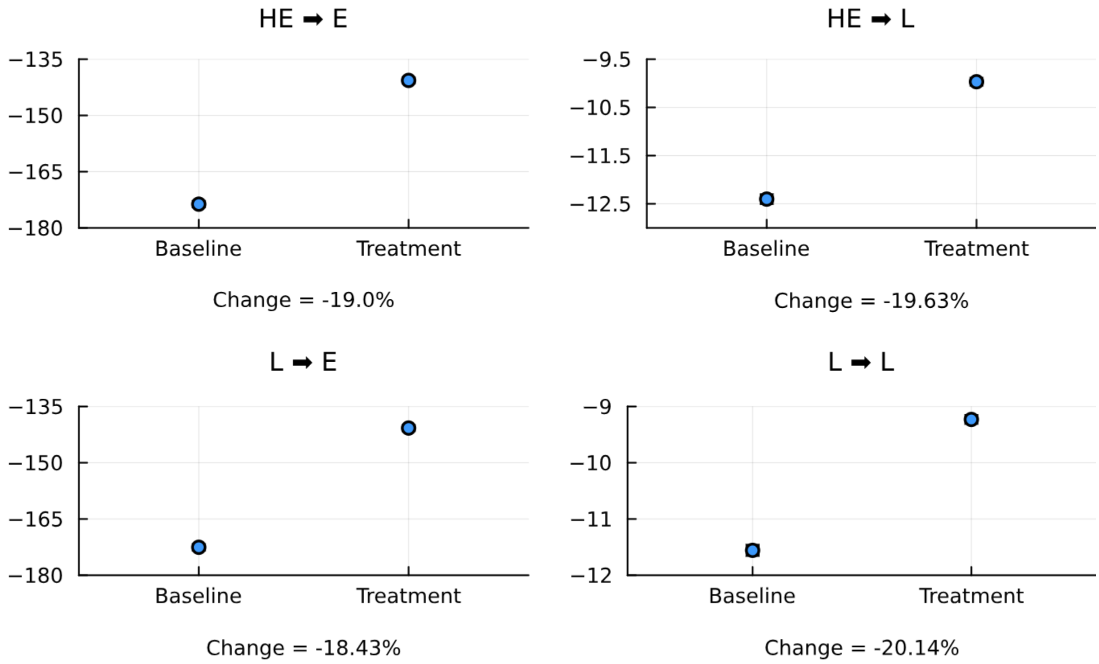
Figure 6: Impact of SSR on return crash pattern




As a first step, it is focused on the effectiveness of SSR in containing crash return patterns. Figure 6 contains the maximum negative returns and the frequency of occurrence of extreme returns, expressed as the coefficient per one hundred periods. Extreme negative returns are defined as $r < -3$ percent, as this threshold is equivalent to twice the standard deviation of returns. It can be observed that SSR reduces the extent of both variables. The maximum negative returns decrease from the baseline to the treatment by 21.88 percent, from 5.07 to 3.96 percent. The frequency of extreme negative returns also drops from 9.17 to 6.54 occurrences of extreme price falls per one hundred periods, representing a 28.69 percent decrease.

In the next step, the underlying behavioral spirals leading to crashes and extreme price returns are examined in detail. As elaborated, excessive price crashes are caused by the behavior of financial market participants and network effects that can result in vicious spirals. It is worth noting that SSR's potential effectiveness in mitigating these propagation effects also underscores its relevance within the context of systemic stability. The interaction channels, as delineated in the model and illustrated in Figure 3, along with the corresponding exemplary story, form the basis of this analysis.

Figure 7: Impact of SSR on sell order interactions




In Figure 7, the impact of SSR on the self-referential and mutual effects of selling orders on both sides of the Figure 3 is depicted. Specifically, the order sizes shaded green in the chart serve as analysis variables. As market crashes are extreme downward scenarios, the maximum sell orders are considered. At this point, it is also valuable to recall that only swing traders are affected by the restrictions since the bank only adjusts its position. To track the effects of herding toward extrapolate behavior, the sell order sizes by the bank and swing traders using chart analysis are collected. If chart analysis was the dominant strategy in the previous period, the collective order size of traders using it was negative. This provides a metric that jointly allows the capture of the effect of the trade order and the market share size of chartists. Likewise, the impact of the leverage adjustment sell orders is measured using both trade order sizes if the leverage adjustment order was negative in the previous period.

First, it is focused on the effects of herding toward extrapolate behavior. The imposition of SSR brings about a notable shift in the maximum sell orders executed by chartists following a negative period with dominant chartism (HE $\rightarrow$ E). With a significant decrease of -19.0 percent, from -173.66 to -140.66. In parallel with the enactment of bans, there is a reduction of

19.63 percent in the maximum leverage adjustment trade size following a period of dominant chartism (HE $\rightarrow$ L), from a baseline mean of -12.4 to -9.97. Now the indirect effects of SSR on deleveraging orders and its impact on itself and extrapolate selling are scrutinized. The findings indicate a decrease in the maximum trade order sizes. The values for the maximum negative order size by agents adhering to the chartists' rule (L $\rightarrow$ E) witness a decrease of -18.43 percent, from -172.54 to -140.74. Similarly, the metric for the bank's maximum negative order size (L $\rightarrow$ E) decreased from -11.56 to -9.23 under treatment by -20.14 percent.

Ultimately, to gauge the effect of SSR's negative market distortion on crash severity, the market distortion BF is examined. Distortion serves as a critical metric as it illustrates the deviation from the intrinsic value. Distortion is measured as the percentage difference of the price to F. The average and maximum values are specifically measured. The former is intended to give a general impression, and the latter to show extreme cases.

Figure 8: Impact of SSR on price distortion metrics

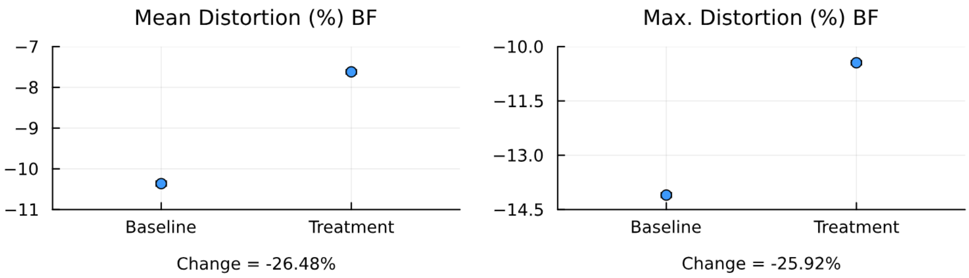
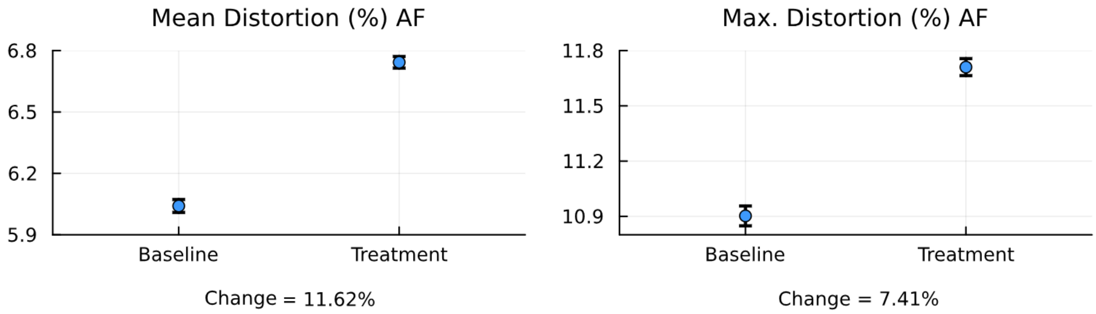



Figure 8 presents an overview of distortion metrics below the intrinsic value. Due to SSR, the mean distortion exhibits a decline of -26.48 percent from -10.36 to -7.62 percent. Further, negative maximum distortion decreases from -14.1 to -10.45 percent, and hence by -25.92 percent in response to SSR.

### 3.2.2 Analysis of Concerns

Given the widespread concerns about the implementation of SSR, including price inflation and subsequent price crashes when SSR are repealed, the subsequent analysis examines to what extent these worries are justified. The measures cover distortion above the fundamental value, the return behavior both above and below the fundamental value, and an analysis of short-term price trends following the repeal of SSR.

Figure 9: Impact of SSR on crash pattern

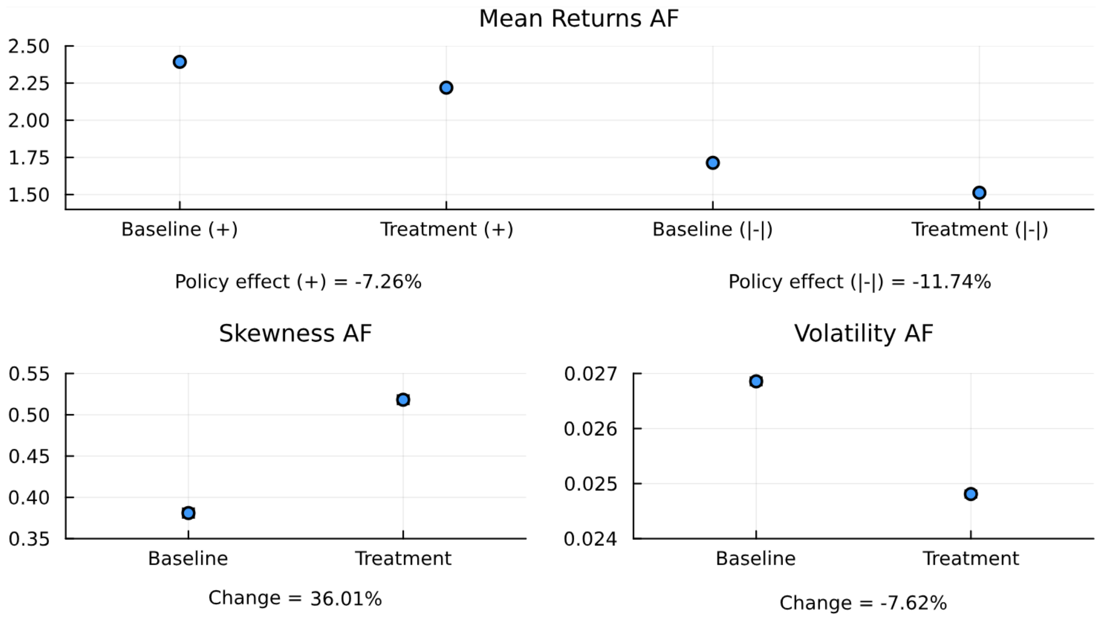



As elaborated at the beginning, the literature suggests that prices will be positively distorted. Figure 9 presents an overview of mean and maximum distortion metrics above F and unveils significant price elevations. Specifically, the mean distortion increases by 11.62 percent from 6.04 percent to 6.74 percent. Similarly, the baseline maximum registers at 10.9 percent, and the treatment maximum is at 11.71 percent, which represents a rise of 7.41 percent.

Moving on, this analysis extends to scrutinizing return patterns by distinguishing returns above and below the fundamental value. The aim is to obtain a picture of the impact of SSR on the price discovery process and, therefore, price efficiency. Recall that positive and negative movements have a corrective or distorting effect depending on whether they occur above or below the fundamental price. Negative values are depicted in absolute figures to facilitate a graphical comparison between positive and negative return values. Additionally, the skewness and volatility are provided for context. Volatility is computed as the standard deviation of the returns.

Figure 10 contains the metrics for the AF case. The returns show a skewness of 0.38 in the baseline scenario and 0.51 under SSR. This corresponds to a 36.01 percent increase. Both positive and negative returns decline in their means. The values decrease due to the SSR from 2.39 percent and 1.71 percent to 2.21 percent and 1.51 percent, by -7.26 percent and -11.74 percent for the positive and absolute negative returns, respectively. Accordingly, the volatility decreases slightly by -7.62 percent from a mean value of 0.027 to 0.025 as a result of the SSR.

Figure 10: Impact of SSR on returns metrics AF




In Figure 11, the same variables are depicted for the BF case. Here, the baseline returns show a negative skewness of -0.15. Yet, the metric flips around to a mean of 0.08 under SSR. Again, both positive and negative returns exhibit a decrease in their averages. Specifically, under SSR, the means slip from 2.11 percent and 2.27 percent to 1.96 percent and 1.92 percent, respectively, corresponding to declines of -7.29 percent and -15.46 percent. Consequently, volatility is experiencing a decline again, transitioning from a 0.029 return standard deviation to 0.026, representing a decline of 11.95 percent.

Ultimately, to address concerns about bubbles emerging and bursting after restrictions are repealed, market drift in the post-treatment control phase is examined using skewness and price level ratios. These ratios capture price level shifts from the price at the lifting of the ban to the mean and median prices in the control phase, presented in compact, standardized metrics. Additionally, comparing these ratios helps account for potential deviations from the mean.

Table 2: Market drift measures

| Skewness | $P_{Median}/\,P_{Repeal}$ | $P_{Mean}/\,P_{Repeal}$ |
|---|---|---|
| 0.4063 | 1.0038 | 1.0044 |

Figure 11: Impact of SSR on returns metrics BF

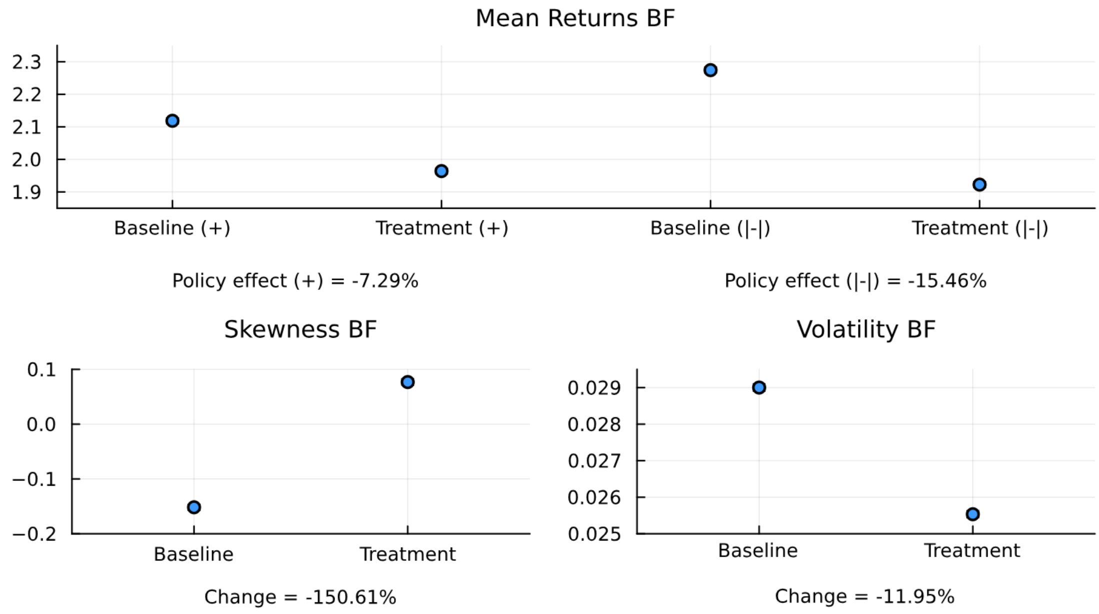


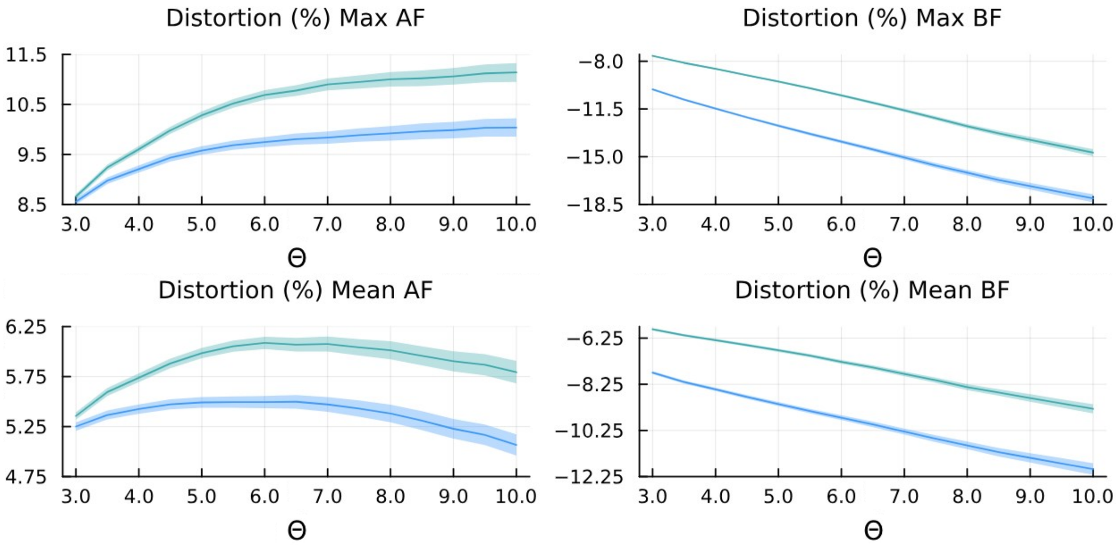

Table 2 sheds light on the repercussions of the lift of SSR on price drift ratios and skewness. After the repeal of the SSR, the mean price drift ratio and the median price drift ratio have values of 1.0038 and 1.0044, respectively. The skewness of the returns is 0.4063. Uniformly, these metrics indicate a modest positive market trend on average in the control periods.

### 3.3 Sensitivity analysis

To test SSR's effects of their sensitivity towards variations in the previously used policy parameter values and for the purpose of supporting prudent and effective policy design, the distortion metrics as leading indicators are subsequently computed for different values of the enactment return threshold and the ban period length. The simulation is run 5000 times for each parameter value, and the resulting mean values for the corresponding metrics are then presented as graphs, in blue for the baseline and green for the treatment case, with shaded areas around representing 95 percent confidence intervals. When examining the plots, it is essential to note that changes in insertion threshold and insertion length also lead to measurement effects. These are noticeable through changes in the baseline graphs. Changes in the policy effect are, in turn, indicated by the relationship between the treatment graphs and the baseline control graphs.

The policy threshold ($\Theta$) refers to the question for regulators of when it is best to impose restric-

Figure 12: Enactment threshold sensitivity of SSR effects on market distortion metrics.




tions and what difference it potentially makes. Accordingly, it is varied, starting with what is commonly considered an extreme return, that is, a return value of more than twice the standard deviation of the returns, corresponding to about a 3 percent return in the model. The endpoint is set at -10 percent. This corresponds to the level at which a form of short-selling restriction is automatically triggered in the US if it materializes within one day, according to SEC Rule 201 (Securities and Exchange Commission, 2010).

Figure 12 illustrates the market distortion metrics as $\Theta$ increases. The RHS plots display the maximum and mean distortion metrics AF. In the upper chart, the maximum plot shows the baseline rising from 8.56 to 10.04 percent, while the policy treatment increases from 8.65 to around 11.14 percent. Below, the mean metrics show a slightly different picture. The baseline graph begins at 5.25 percent, initially exhibits a slight increase, and then declines to 5.07 percent. The treatment plot behaves similarly, starting at 5.36 percent. However, it shows an ultimate increase and ends at 5.79 percent. All plots exhibit a common concave shape, with the gap between the baseline and treatment widening initially and then remaining relatively constant. The RHS plots contain the graphs for the BF case. All metrics decay almost in parallel. For the maximum metrics, the baseline decreases from -10.06 percent to -18.05 percent, and the policy treatment drops from -7.61 percent to -14.7 percent. Regarding the mean metrics, the baseline falls from -7.75 percent to -11.92 percent, while the treatment declines from -5.87

percent to -9.32 percent. The gaps in both plots exhibit only a very slight widening, indicating a rather consistent policy effect.

While the economic interpretation of the results follows in the next section, at this point, a few technical notes are provided to explain the variation in the baseline plots due to measurement effects. The concave shape of the curves for the AF case may initially seem odd; however, when considered in the context of Figure 4, it is only logically consistent. Only the upward orientation of the maximum plots remains unexpected. However, this can be attributed to the fact that higher returns are more likely to occur in the high-volatility regime, with higher variability also leading to higher maximum values.

Another important consideration for policymakers is the length of measures and, accordingly, the impact beyond the short term. Thus, the goal of the following analysis is to gain insight into the medium-term effects. In technical analysis, "medium-term" refers to a time frame spanning several weeks to several months. Hence, the sensitivity analysis varies the length from 10 to 80 periods in 15 steps. With five periods equal to one trading week, the ban length ($\Lambda$) is varied from two weeks to four months.

Figure 13: Ban duration sensitivity of SSR effects on market distortion metrics.

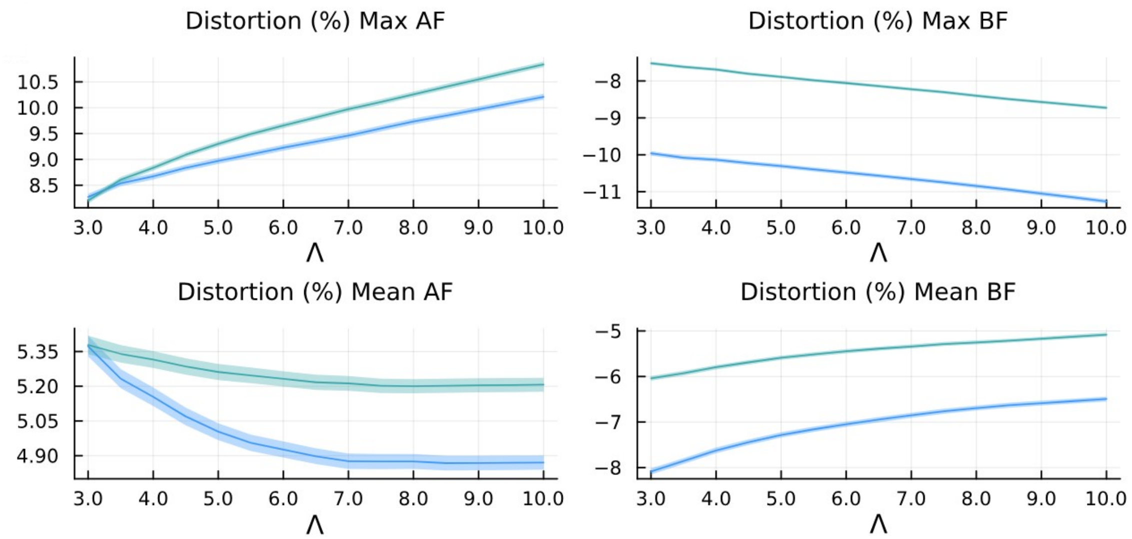



Figure 13 contains results on market distortion as $\Lambda$ is increased. In the top left graph, the baseline maximum distortion AF rises from 8.27 to 10.21 percent. Under the policy treatment, it

rises more, from 8.2 to 10.84 percent, indicating consistently higher distortion and an increasing policy effect as $\Lambda$ increases. Below are the graphs for the mean values AF, both of which demonstrate a convex shape. The baseline graph decays from 5.37 to 4.87 percent and then stabilizes, whereas the policy graph declines only slightly from 5.38 to 5.21. This results in an initially widening gap, which then remains steady. In the plots to the right, the distortion metrics BF are depicted. Both cases for the maximum metrics show a constant decaying trend in parallel to each other. The baseline decays from -9.96 percent to -11.26 percent. The policy treatment graph ranges from -7.52 percent to -8.73 percent. The graphs below illustrate the mean distortion values of BF. In the baseline scenario, the mean metric rises from -8.08 percent to -6.49 percent. Under the policy treatment, the mean metric similarly transitions from -6.04 to -5.08 percent. The distance between the plots stays relatively steady as $\Lambda$ is varied.
Again, the conspicuous shapes, unrelated to the relationship between the scenario plots, are briefly discussed. In this instance, the mean and maximum graphs exhibit divergent trends. The trend of the maximum extreme values can be readily explained, as a longer time period allows for a greater potential to reach higher maxima. Conversely, the mean values depict the overall dynamics; thus, it is equally unsurprising that, with an extended time span, a reversion trend towards the fundamental value occurs.

# 4 Discussion

The findings in the previous section contain valuable implications against the background of the research question for further research and policy decisions. The results in Figure 8 indicate that the implementation of SSR leads to a decrease in distortion for maximum values and means below the fundamental value. This confirms the finding of previous works that prices are inflated when SSR are introduced. When examining the results from the perspective of price stability, it can be stated that this price increase equals a price stabilization below the fundamental value. Since the negative distortion is significantly reduced, it can be stated that SSR represent an effective tool to reduce the severity of market crashes. Additionally, the simultaneous decrease in the frequency of extreme returns and the magnitude of maximum realized returns emphasizes the fact that SSR mitigates market crash dynamics.

This can be attributed to the results in Figure 7, which indicate that SSR can curb detrimental behavioral spirals. Under SSR, the maximum sale order sizes are uniformly reduced by roughly 20 percent. While the order sizes of swing traders are directly affected by the ban, leverage adjustments are reduced through the described channels. Specifically, restricting extrapolate sell orders leads to fewer and less strong negative price movements. This reduces the profits of chart analysis, its relative attractiveness, and, in turn, its strategy share and pull force through the herding effects. In addition, fewer sharp price falls lead to fewer high devaluations of the asset portfolio and an increase in the VaR risk measure for the bank. Both of these factors reduce the adjustment orders. Again, the result is fewer and weaker negative price movements, which underlines the stabilizing effect of SSR on the financial market. At the same time, additionally, the importance of SSR for systemic stability becomes particularly apparent, and it is therefore rightly taken into account in the policy area of macro-prudential regulation, as these network effects are contained. This being said, the given setup is an isolated market with one representative leveraged trader, but in reality, the financial sector consists of multiple interconnected markets with multiple leveraged traders. Thus, in reality, the behavioral network effects leading to vicious selling cycles are spreading across markets. Therefore, it would be interesting to analyze the effect of SSR in agent-based models with at least two markets to control for policy externalities, as e.g. Westerhoff and Dieci (2006) do for the Tobin tax and also with more leveraged traders. The results obtained so far align with the widely accepted view in the literature that SSR downward constrain the price discovery process. In this context, the detrimental effects on price efficiency are often emphasized. The return analysis, split into cases above and below the controlled intrinsic asset value, offers a more complete picture of the effects on efficiency. The treatment estimates demonstrate that, in both maximum and mean terms, positive and absolute negative returns above and below the fundamental value are consistently decreased. As in both areas, volatility is tamed, the reduction in positive returns, in turn, can be comprehended as a consequence of a general calming of the market. Yet, only the net policy effect matters for the convergence to F, and in both cases, the negative price movements are more significantly affected than the positive ones. This seems to be intuitive, as these are affected by SSR. As a result, the skewness increases in both analysis areas, indicating a positive market drift. Although this means that downward price discovery is hindered above the fundamental value, it also highlights the effectiveness of SSR in enhancing price stability and efficiency below the fundamental value. In addition, when comparing the Figure 8 and Figure 9, it becomes apparent that the supportive effect below F is stronger than the bubble effect above it. This asymmetry constitutes a novel finding and indicates that SSR lead to a net positive social benefit.

This has important implications for researchers and policymakers. For empirical analysis, it emphasizes the importance of controlling for over- and under-valuation effects when scrutinizing the repercussions of SSR, for example, using proxies as price-earnings ratios. Even though they are flawed proxies, they might help to avoid strong biases. Likewise, regulatory authorities must also consider that extreme negative price returns in overvalued markets can be healthy.

The tests of the policy for different policy parameters yield similar indications. In Figure 12, where the enactment threshold is varied, the graphs for the AF case show an initially widening and therefore strengthening policy effect. This can be linked to the policy being implemented, also already in the low volatility regime, in which there are no trends to be broken. While the conclusion of this might be to avoid precautionary pro-activism and hence distortion, the implications of the results relating to the BF case are quite the opposite. Although the plots do not show a substantial increase in the policy effect. Against the background of the accelerating nature of the behavioral spirals, the downward slope can not be understood solely due to the measurement points. Still, one can also infer that early interventions might prevent more extreme dynamics. Consequently, the appropriate policy response hinges on whether the asset is perceived as overvalued or undervalued.

In Figure 13, where the policy is applied for different durations, the AF case shows an increasing gap. This is because above F the threshold is less likely to be triggered by random incidents, rather than by systemic downward spirals. Consequently, there is less downward pressure to mitigate by the SSR, and it takes longer for the effect to unfold. Below F however, the effect is relatively constant. Another observation is that maximum metrics stray away from F and mean metrics towards it with increasing ban length. This indicates that as more time passes, increasingly extreme values are realized, but also that the market exhibits a self-recovery force, which becomes apparent in the mean.

Therefore, policy recommendations are ambivalent. There seems to be a general tendency for market recovery and no need for unnecessary friction in the market. At the same time, it can be seen that extreme scenarios are realized, which might want to be prevented. In the end, the regulatory authorities have to evaluate and decide not only about the correct valuation but also whether a downward trend is sustainably broken, or whether there is a necessity for further support of the correction, considering external market factors such as uncertainty, pessimism, and systemic stability concerns.

With this in mind, it is essential to acknowledge the hazards associated with emerging bubbles due to SSR. The results presented in Table 2 indicate that within the model, no crashes occur during the control phase after treatment. On the contrary, the skewness of the returns is positively biased, and the price level ratios also hint at an upward trend. The slight difference between the median and mean price ratios additionally suggests that price movements are likely to be relatively linear, without significant downward deviations.

As a continuation of the price trends is seen, it can be stated that the concerns about bursting bubbles are not universally applicable and should not be overestimated. Yet, all presented estimates are mean values of multiple simulations. This explicitly does not rule out the possibility that crash scenarios occurred during the simulation runs after a ban lift, and similarly, this could occur in reality. In addition, there is the possibility of excess hysteresis. As for every model of this kind, the results are subject to the Lucas critique, meaning that the reaction of agents might deviate in reality. Against this background, the risks associated with bubble formations should not be entirely neglected in policy decisions.

Another important regulatory consideration concerns risk factors such as manipulative and predatory short-selling, which are difficult to quantify. In the model, strong disturbance terms initiating downward trends may be interpreted as short or bear raid attacks, though such behavior is not explicitly modeled. Neither is the potential deterrent force that credible regulatory authorities with the competence to deploy SSR have considered. Incorporating these aspects offers another promising avenue for future research. Even if empirical studies find no preventive effect of SSR, the threat of such attacks persists, and the unquantifiable deterrent effect may create a policy prevention paradox that misleads results.

# 5 Conclusions

This paper examines the impact of short-selling constraints on financial stability and efficiency during times of stress. The analysis was conducted in an agent-based financial market model that explicitly controls for the fundamental value and incorporates the primary behavioral drivers of crashes, namely herding, extrapolate trades and pro-cyclical deleveraging. This framework allows a direct assessment of the stabilizing and destabilizing forces of SSR in comparison to the benchmark of the fundamental value. Three key results stand out. First, SSR are effective in mitigating severe downward distortions. This finding directly addresses regulators' primary objective of preventing crashes. Second, by distinguishing between dynamics above and below the fundamental value, the analysis reveals a novel asymmetry. While short-selling restrictions impair downward price discovery and thereby elevate prices above fundamentals, their effect below fundamentals is more pronounced: they dampen both the size and frequency of extreme negative returns and facilitate corrective adjustments back toward the fundamental value. This previously undocumented asymmetry generates a net efficiency gain in the model and offers a new contribution to the debate on the efficiency implications of short-selling restrictions. Third, the study shows that SSR weaken the propagation channels that amplify crashes. The interaction between herding dynamics and leverage adjustments is substantially dampened, leading to smaller selling orders in extreme states. In this way, SSR contribute not only to asset price stability but also to systemic stability by containing destabilizing feedback loops. Taken together, these findings suggest that SSR should be viewed as a valuable emergency tool that can deliver net social benefits by stabilizing prices below the fundamental value and mitigating systemic feedback effects in times of stress.

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# Appendix A - The bank's trading rule

This section elaborates on how the bank risk-adjusts its position as a long-term investor. For this purpose, it is worth recalling the basic ideas already presented in section 3.3. The bank strives to achieve a specific leverage ratio denoted as $LR_t^{Tar}$ based on the scaled RiskMetrics VaR, following Aymanns and Farmer (2015) closely.

$$LR_t^{Tar} = \Psi VaR_t = \frac{DB_t}{E_t} \tag{21}$$

Before exploring how the bank adjusts its position. All required accounting variables are properly introduced. Starting with the portfolio value, $AV$, held by the bank at time $t$, which is computed by multiplying the assets by the current market price. This is shown in the following equation:

$$AV_t = AS_t^B P_t \tag{22}$$

The asset stock, $AS$, of bank, $B$, at time, $t$, is determined by adding the trade order of the current period to the assets held in the previous period. The following equation expresses this:

$$AS_t^B = AS_{t-1}^B + D_t^B \tag{23}$$

On the other side of the bank's balance sheet are the equity and debt. The equity, $E_t$, represents its net worth and is computed by subtracting its debt from the market value of its assets. The equation is:

$$E_t = AV_t - DB_t \tag{24}$$

Given that it is presumed that the bank operates with leverage, or in other words, uses debt, viewing the account as a debt balance is more convenient. The debt balance, $DB_t$, is found by subtracting the current period's currency flow from the previous period's debt amount.

$$DB_t = DB_{t-1} - CF_t \tag{25}$$

The movement of funds into and out of the bank due to its transactions in the market is represented by the currency flow, $CF$. At the time $t$, the currency flow is calculated as the product of $D_t^B$ and $P_t$, with a negative sign as a purchase makes money go out and vice versa.

$$CF_t = -(D_t^B P_t) \tag{26}$$

At this point, the leverage targeting, and hence the trading orders of the bank, $D_t^B$, move back into focus. Although the bank is aware that the price will change, following on from the assumption of the RiskMetrics approach that the returns are zero on average, the bank uses static forecasting for the price in the coming period, therefore applies $P_{t-1} = P_t^e$ as best proxy of a long term investor for short-term fluctuation. Accordingly, the bank expects:

$$LR_{t-1}^{Tar} = \frac{DB_{t-1}}{E_{t-1}} = LR_t^{Tar}$$

Note, that since equity is a function of the portfolio value and the debt amount. The bank actually aims to adjust its debt level, to meet $LR_t^{Tar}$. Against this background, $DB_{t-1}$ can be understood as implied debt target, $DB_{t-1}^{Tar}$.

Yet, the asset price changes at the end of every period; this has two effects on the bank's account. On the one hand, does every return also affect the VaR measure and hence $LR_t^{Tar}$ deviates. On the other hand, the price affects the portfolio value, and hence the bank's equity, $E_{t-1}$, changes; as a result, equation (21) no longer holds. Both effects cause the bank to deviate from its targeted leverage ratio, determined in the previous period.

$$LR_t^{Tar} \neq \frac{DB_{t-1}}{E_{t-1}}$$

Thus, the bank readjusts its position in every period. To derive the bank's trading rule, let's commence by considering the target leverage ratio. As first step, equation (21) is taken and the equations (23), (22), (24), (25) and (26) are plugged in. As $D_{t+1}^B$ is set to readjust the portfolio correctly using static forecasting, it applies:

$$LR_t^{Tar} = \frac{DB_t}{E_t} = \frac{DB_{t-1} + (D_t \cdot P_t^e)}{(AS_{t-1} - D_t^B) \cdot P_t^e - (DB_{t-1} - D_t^B \cdot P_t^e)}$$

The goal is to isolate $D$ in this equation to determine the number of stocks the trader should sell in order to meet their target leverage ratio.

$$D = \frac{-DB_{t-1} + LR_t^{Tar}(AS_{t-1}P_t^e - DB_{t-1})}{P_t^e}$$

Since $P_t^e = P_{t-1}$ and $(AS_{t-1} * P_{t-1} - DB_{t-1})$ equals the static equation of equity ($E$) at $t-1$, it can be substituted to further reduce the equation.

$$D = \frac{-DB_{t-1} + LR_t^{Tar}E_{t-1}}{P_t^e}$$

Now, to obtain an equation that allows for economic interpretation, let's rearrange this equation a bit more. Given that $LR = \frac{DB}{E}$, we can rearrange it to $DB = LR * E$. As described above, $LR_t \cdot E_{t-1}$ can be understood as the debt target $DB_t^{\text{Tar}}$. Accordingly, it expresses the amount of assets that have to be bought or sold to make the current debt equal to the target debt. Hence, $LR_t = LR_t^{\text{Tar}}$ under the assumption that $P_{t-1} = P_t$.

$$D_t = \frac{DB_t^{\text{Tar}} - DB_{t-1}}{P_t^e}$$

# Appendix B: Stylized facts under treatment

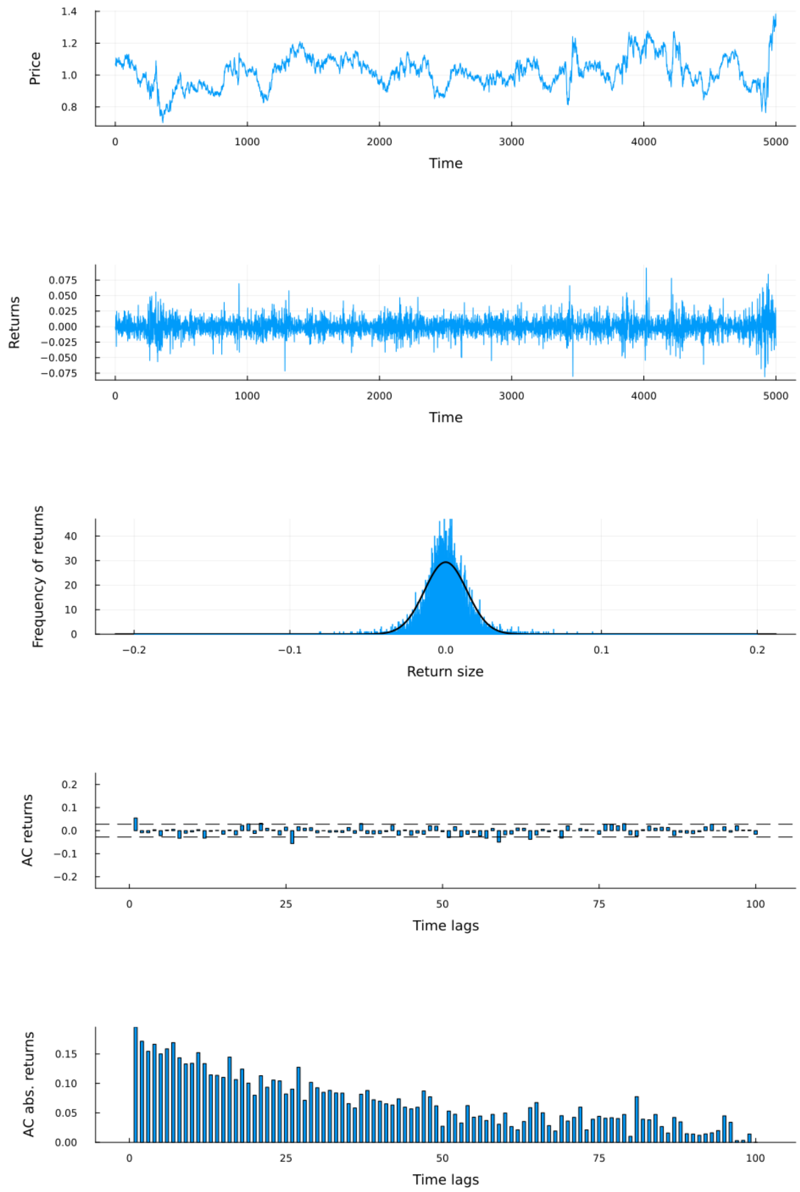


Figure 14: The illustrations above depict the stylized financial market characteristics under the regulatory regime

# Appendix C: Variable design

This section provides the detailed mathematical formulations used to calculate the observational variables discussed in the main body of the paper. There the presented metrics are compared as means across numerous repetitions. However, this section focuses solely on the formulas illustrating the method for computing values obtained from a single simulation run to ensure transparency and reproducibility.

Let's recall that the relevant variables are tracked throughout the observatory phases. The number of these subsets is denoted by $J$ and indexed by $j$. Observations within each subset are indexed by $t$ and the length of each observatory phase is represented by $T$. However, for metrics such as skewness and standard deviation, calculations are based on the aggregated values from all sub-samples. This approach is necessary because individual sub-samples are too small, making estimates potentially unreliable and heavily influenced by outliers.

### 5.0.1 Distortion Analysis

The distortion metrics for mean and maximum values above and below the fundamental value are all based on the computation of the price bias in every single period. This is given with the percentage deviation of the price to the fundamental value:

$$\Delta_t = \left(\frac{P_t - F}{F}\right) \times 100$$

Let the subsets of the observatory periods be denoted by $\Delta_{sub}$ and the subsets filtered for positive distortion above the F and negative distortion below F as $\Delta^+_{sub}$ and $\Delta^-_{sub}$, respectively. The corresponding set of these samples for an entire simulation run is given by $\Delta^+_{run}$ and $\Delta^-_{run}$

$$\Delta^+_{sub} = \{\Delta_t \in \Delta_{sub} \mid \Delta_t > 0\}, \quad \Delta^+_{run} = \{\Delta^+_{\text{sub}_j}\}_{j=1}^{J}$$

$$\Delta^-_{sub} = \{\Delta_t \in \Delta_{sub} \mid \Delta_t < 0\}, \quad \Delta^-_{run} = \{\Delta^-_{\text{sub}_j}\}_{j=1}^{J}$$

Accordingly, the formulas for the mean and maximum distortion above the F, as well as the mean and minimum distortions below the fundamental value, are as follows:

$$\text{Mean distortion (AF):} = \frac{1}{J}\sum_{j=1}^{J}\frac{1}{T}\sum_{t=1}^{T}\Delta_t(\Delta_t > 0)$$

$$\text{Maximum distortion (AF):} = \frac{1}{J}\sum_{j=1}^{J}\max(\Delta^{+}_{\text{sub}_j})$$

$$\text{Mean distortion (BF):} = \frac{1}{J}\sum_{j=1}^{J}\frac{1}{T}\sum_{t=1}^{T}\Delta_t(\Delta_t > 0)$$

$$\text{Maximum distortion (BF):} = \frac{1}{J}\sum_{j=1}^{J}\min(\Delta^{-}_{\text{sub}_j})$$

### 5.0.2 Price level ratios

Transitioning to the price level ratios, let's recall that for all three fractions a metric (exit price, mean and median) is set in relation to the entry price. That is the first price of an observation period. The price samples of these phases are given by $\Pi_{sub}$ and the collective set of sub-samples of an entire simulation run by $\Pi_{run}$.

$$\Pi_{sub} = \{P_t\}_{t=1}^{T}, \quad \Pi_{run} = \{\Pi_{sub}\}_{j=1}^{J}$$

This being said, the price level ratios are computed as follows:

$$\text{Entry/Exit Ratio} = \frac{1}{J}\sum_{j=1}^{J}\frac{P_T}{P_1}$$

$$\text{Entry/Mean Ratio} = \frac{1}{J}\sum_{j=1}^{J}\frac{\frac{1}{T}\sum_{t=1}^{T}P_t}{P_1}$$

To calculate the median of the sub-samples ($\widetilde{\Pi}_{\text{sub}}$), the elements within each sub-sample are arranged in ascending order, thereby altering their respective indices. Let $P_i$ denote the elements organized in ascending order such that $P_1 < P_2 < \ldots < P_N$, where $N$ represents the length of the samples and their highest element. Accordingly, the middle positions of the series are given by n=N/2 and m=(N/2)+1.

$$\widetilde{\Pi}_{\text{sub}} = \begin{cases} P_m & \text{for odd } N \\ \frac{P_n+P_m}{2} & \text{for even } N \end{cases}$$

$$\text{Entry/Median Ratio} = \frac{1}{J}\sum_{j=1}^{J}\frac{\widetilde{\Pi}_{\text{sub, j}}}{P_1}$$

### 5.0.3 Return Analysis

Returns are computed in each period as a percentage change from $P_{t-1}$ to $P_t$.

$$r_t = \frac{P_t - P_{t-1}}{P_{t-1}} \times 100$$

The return analysis covers mean negative and positive returns as well as the skewness and volatility above and below the fundamental value. The samples for negative and positive returns above and below the fundamental value are given by:

$$R_{\text{sub}} = \{r_t\}_{t=1}^{T}, \quad R_{\text{run}} = \{R_{\text{sub}_j}\}_{j=1}^{J}$$

$$\text{Mean positive returns (AF):} = \frac{1}{J}\sum_{j=1}^{J}\frac{1}{T}\sum_{t=1}^{T} r_t(r_t > 0 \wedge P_t > F)$$

$$\text{Mean positive returns (BF):} = \frac{1}{J}\sum_{j=1}^{J}\frac{1}{T}\sum_{t=1}^{T} r_t(r_t > 0 \wedge P_t < F)$$

$$\text{Mean absolute negative returns (AF):} = \frac{1}{J}\sum_{j=1}^{J}\frac{1}{T}\sum_{t=1}^{T} |r_t|(r_t < 0 \wedge P_t > F)$$

$$\text{Mean absolute negative returns (BF):} = \frac{1}{J}\sum_{j=1}^{J}\frac{1}{T}\sum_{t=1}^{T} |r_t|(r_t > 0 \wedge P_t < F)$$

Let's recall the crash pattern variable set, encompassing the simulation means of the maximum negative return, an occurrence rate for extreme returns denoted as $\chi_{\text{count}}$

$$\text{Maximum absolute negative return:} = \frac{1}{J}\sum_{j=1}^{J} |\min(R_{\text{sub}_j}|)$$

$$\chi_{\text{count}} = \frac{1}{J}\sum_{j=1}^{J}\left(\frac{100}{T}\right)\sum_{t=1}^{T} 1(r_t < \theta)$$

As previously articulated, the skewness and volatility are computed using the united sample that incorporates all individual sub-samples.

$$R_{sub}^{AF} = \{r_t \in R_{sub} \mid P_t > F\}, \quad R_{run}^{+,AF} = \bigcup_{j=1}^{J}\{R_{sub}^{+,AF}\}$$

$$R_{sub}^{BF} = \{r_t \in R_{sub} \mid P_t < F\}, \quad R_{run}^{+,BF} = \bigcup_{j=1}^{J}\{R_{sub}^{+,BF}\}$$

This being said, for the skewness of the control phases after the bans, it is not distinguished between above or below F, this sample is given by $R_{sub}$.

$$R_{\text{sub}} = \{r_t\}_{t=1}^{T}, \quad R_{\text{run}} = \bigcup_{j=1}^{J} R_{\text{sub}_j}$$

The skewness follows the standard calculation. The symbol s stands for the standard deviation of the return series.

$$\text{Skewness} = \frac{J}{(J-1)(J-2)}\sum_{j=1}^{J}\left(\frac{r_j - \bar{r}}{s}\right)^3$$

$$\text{Volatility} = \sqrt{\frac{1}{J-1}\sum_{j=1}^{J}(r_j - \bar{r})^2}$$

### 5.0.4 Crash Dynamics Analysis

To track the effects of herding toward extrapolate behavior, the sell order sizes by the bank and swing traders using chart analysis are collected if chart analysis was the dominant strategy in the previous period and the collective order size of traders using it was negative. The aggregated orders by swing traders using chart analysis is given by:

$$D_t^{CA} = \sum_{i=1}^{N} D_t^i \cdot (I_t^i = CA)$$

Building upon this, the samples for variable HE→E are given by $EE_{sub}$ and $EE_{run}$ as well as for HE→L by $EL_{sub}$ and $EL_{run}$.

$$EE_{sub} = \{D_t^{CA} \mid D_{t-1}^{CA} < 0 \land H_{t-1}^{CA} > H_{t-1}^{FA}\}, \quad EE_{run} = \{EE_{\text{sub}_j}\}_{j=1}^{J}$$

$$EL_{sub} = \{D_t^{B} \mid D_{t-1}^{CA} < 0 \land H_{t-1}^{CA} > H_{t-1}^{FA}\}, \quad EL_{run} = \{EL_{\text{sub}_j}\}_{j=1}^{J}$$

Likewise, the effect of the leverage adjustment sell orders is measured using both trade order sizes, if the leverage adjustment order was negative in the previous period. The sub-samples for variable L→E is given by $LE_{sub}$ as well as for L→L by $LL_{sub}$. The sets for the entire runs are given by $LE_{run}$ and $LL_{run}$ respectively.

$$LE_{sub} = \{D_t^{CA} \mid D_{t-1}^{B} < 0\}, \quad LE_{run} = \{LE_{\text{sub}_j}\}_{j=1}^{J}$$

$$LL_{sub} = \{D_t^{B} \mid D_{t-1}^{B} < 0\}, \quad LL_{run} = \{LL_{\text{sub}_j}\}_{j=1}^{J}$$

Pursuant to this, the estimates are given.

$$\text{HE}{\rightarrow}\text{E} = \frac{1}{J}\sum_{j=1}^{J}\min(EE_{\text{sub, j}})$$

$$\text{HE}{\rightarrow}\text{L} = \frac{1}{J}\sum_{j=1}^{J}\min(EL_{\text{sub, j}})$$

$$\text{L}{\rightarrow}\text{E} = \frac{1}{J}\sum_{j=1}^{J}\min(LE_{\text{sub, j}})$$

$$\text{L}{\rightarrow}\text{L} = \frac{1}{J}\sum_{j=1}^{J}\min(LL_{\text{sub, j}})$$

# Paper 2

# Stress-testing Inflation Exposure: Systemically Significant Prices and Asymmetric Shock Propagation in the EU


**Publication status and bibliographic information**

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**Abstract**

This paper documents asymmetries in price shock exposure for the EU, EU core and periphery within the global production network. Building on the foundational work of Weber et al. (2024a), we run a cost-push stress-test using data from the World Input–Output Database to estimate a region's exposure to globally originating and propagating price shocks. We confirm the existence of systemically significant sectors which dominate the overall price level. While the final-goods price effects of various sectors are significant, about half are the result of higher-order propagation. This indirect effect is even larger for peripheral countries. Tracing disaggregated shock trajectories uncovers that price volatility originating in core and non-EU countries impacts the peripheral countries more than vice versa. Simultaneously, our method of recovering consumption substitution effects shows that substitution is more limited in the European periphery. The stark asymmetries in exposure have profound implications for fiscal and monetary policy.


**Author's contribution**

I initiated the project by proposing the research idea. Subsequently, I contributed by drafting initial versions of the introduction, literature review, and parts of the discussion of results. Additionally, I provided a background analysis by applying the IOA price multiplier exercise to each country's CPI. I took on organizational tasks to support the group process and assisted in improving the overall writing style.


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# 1. Introduction

In a globally integrated economy, hardly any region can avoid economic exposure to shocks such as the Covid-19 pandemic or the recent geopolitical conflicts. Yet, the level of exposure may vary substantially depending on the region and type of shock (Chakraborty et al., 2024). This paper aims to uncover latent asymmetries in price shock exposure for the EU, EU core and periphery within the global production network.[1] Building on the foundational work of Weber et al. (2024a), we run a cost-push stress-testing exercise using data from the World Input Output Database to identify a regions' exposure to globally originating and propagating price shocks. Consistent with Weber et al.'s (2024a) findings for the United States, we find a small subset of systemically significant sectors to dominate the price volatility in the EU, EU periphery and EU core. While for most of these sectors, the direct effect of a shock on its respective final goods' prices is substantial, close to half of the total price volatility in our model results from higher-order propagation within the production network. Breaking down the geographical component of price volatility exposure, we show that the indirect propagation effect is larger for peripheral countries. By tracing individual shock trajectories, we find that price volatility propagating from the EU core to the periphery has substantially more impact than vice versa. Moreover, our model suggests that peripheral countries import substantially more price volatility from outside the EU, which suggests them to be more exposed to world market prices. To recover consumption substitution effects, we suggest a decomposition based on Olley and Pakes (1996) and find that while consumers in the EU core are able to partially substitute away from more volatile sectors, consumers in peripheral countries are not. We also suggest a formal operationalization for the existence of systemically significant prices, utilizing the

[1] We decided to include Great Britain in our analysis because of its economic importance and extensive trade relationship with EU countries. For the sake of brevity, we use the acronym EU to refer to the EU countries at the final year of our sample in 2014, thus including Great Britain.

mathematical properties of power law distributions. Our results show that the overall price impact of the most important sectors is well described by a power law distribution with a tail exponent smaller than 2. Therefore, the idiosyncratic destinies of these systemically significant sectors indeed drive aggregate fluctuations of the synthetic CPIs in our model. Finally, a power series approximation allows us to trace the diffusion of shocks by documenting round-to-round effects. Notably, we are able to derive all our results from an in-sample of years with relatively low inflationary pressure and thus overcoming a notorious challenge for stress-tests (Borio et al. 2014).

The remainder of this paper is organized as follows: Section 2 places our findings within the body of related literature. In Section 3, data and methodology of the stress-test are presented. Section 4 showcases our findings, while Section 5 discusses our results. Section 6 concludes and points to some avenues for further research.

# 2. Related literature

Our project relates to several strands of research, some of which sparked (renewed) interest in the wake of the latest supply chain disruptions. Namely, we add to a neglected perspective of the latest calls to stress-test production networks by uncovering the latent inflation exposure in the global production network using an input-output (IO) stress-test framework. Moreover, our work supports efforts to decipher the underlying dynamics of what is widely considered a cost-push inflation resulting from a mixture of recent supply-side shocks. Thirdly, we add to the understanding of differing regional exposures manifested in heterogeneous dependencies between regions.

In the post-Lehman world, stress-tests were soon regarded as a viable tool for authorities to simulate pressure on the financial system and played a crucial role in restoring confidence in the financial system (Herring and Schuermann, 2022). By now, stress-tests are considered indispensable and their much-needed improvement has been prioritized by authorities and researchers alike (Aikmann et al., 2023). Lately, calls to establish macroprudential stress-tests also for supply chains became more prominent (Baldwin and Freeman, 2022; Miroudot, 2020). Naturally, IO models which have commonly been used to conduct disaster impact analysis provide a sensible starting point.[2] As a prominent example, Carvalho et al. (2021) investigate the Great East Japan Earthquake of 2011 and document the relevance of IO linkages in propagating this shock. Closer to an actual stress-test are the works of Diem et al. (2022) and Chakraborty et al. (2024). The authors of the former paper propose and test a novel measure of economic systemic risk of firms in the Hungarian production network. The latter paper shows that richer countries expose poorer countries to significantly more systemic risk than vice versa. Finally, the foundational work of Weber et al. (2024a), unveiled the need to expand the supply-side stress-test call to also assess potential inflation exposure. Challenging the conventional understanding of inflation as an aggregate phenomenon, the authors show a set of few sectors – so-called systemically significant prices[3] – to be the main driver of the overall price level in the US.[4] Moreover, their research suggests that these systemically significant prices could be identified before critical disruptions occur, opening up a broad policy space to address future cost-push shocks (van't Klooster and Weber, 2024). Weber et al.'s (2024a) IO price model

[2] See Galbusera and Giannopoulos (2018) for an overview.
[3] The concept of systemically significant prices was first put forward by Hockett and Omarova (2016).
[4] The insight that shocks of heterogenous origins can trigger aggregate fluctuations in the presence of strongly asymmetric intersectoral IO linkages – as found in empirical production networks – has been increasingly considered following the initial work by Acemoglu et al. (2012). However, expanding this notion to the realm of inflation is in marked contrast to the conventional wisdom of both the Monetarist and New Keynesian approaches that inflation should be understood as an aggregate phenomenon (Galbraith, 2023). Yet, recent theoretical papers in the New Keynesian tradition also implicitly recognize the existence of systemically significant prices by showing that relative price movements might affect aggregate inflation (Afrouzi et al., 2024).

framework, which builds upon the foundational work of Leontief and its application in Valadkhani and Mitchell (2002), has since been successfully applied to disentangle the latest inflationary dynamics (see e.g. Goldztejn (2024) for the French case), simulating scenarios of carbon price inflation (Weber et al., 2024b) or decomposing the asymmetric effects of cost-push shocks on different income groups in the EU (Ipsen and Schulz, 2024; Schulz and Ipsen, 2024). This paper again builds upon this framework to study the geographical dimension of cost-push inflation exposure faced by different regions within the European Union.

Extending Weber et al. (2024a), we embed our stress-test exercise in a global context. Naturally, not only the interconnectedness of firms and sectors within a given economy is of relevance to understand output and inflation dynamics, but also the cross-border linkages to the world economy. Borio and Filardo (2007) find, for example, that the influence of global factors on inflation in OECD countries has been growing over time, particularly since the 1990s due to the increased integration of the world economy.

However, it is also insufficient to merely contrast exposure of the EU vis-à-vis non-EU countries. Given the regional heterogeneity within the EU, a comprehensive analysis of inflation exposure for the EU must also examine latent internal asymmetries in exposure. As several studies have shown, these asymmetries can be substantial. Bayoumi and Eichengreen (1992) provide evidence for the existence of a core-periphery pattern for 11 EU countries and find that, while comparable shocks occur in the core, these are more asymmetric for peripheral countries. Chakraborty et al. (2024), tracing global asymmetries in systemic risk exposure, also identify asymmetries within the EU. Gräbner et al. (2020a, 2020b) again find patterns of asymmetries such as a core-periphery structure for different EU countries.

Figure 1 shows that such a core-periphery structure is also clearly visible in the EU production network (as of 2014). This highlights the need to not only consider the exposure of the EU vis-à-vis non-EU countries but also asymmetric price shock exposure within the EU. Sectors are represented by dots, while links between dots capture trade relationships of more than 385 million USD (smaller links have been omitted for visibility reasons). Clusters (colors) are identified using the Louvain method for community detection and indicate sets of sectors with increased trade relationships. The upper right corner shows a part of the network at further granularity with sector labels according to the ISIC Rev. 4 classification.

Therefore, the analytical perspective of a core-periphery structure is used in this study to analyze the geographical asymmetries in inflation exposure in the EU. Historically, the distinction between core (or center) and periphery first gained recognition through the work of dependency theorists. The classical Keynesian view espoused by Pasinetti (1983, chp. 11) argues that proportional differences in national income between countries manifest themselves into structurally different consumption baskets based on a hierarchy of needs, with essential goods being at the top of the hierarchy. This line of argument resembles a major hypothesis of dependency theorists (Harvey et al., 2010), who argue that substitutability is much more limited for these essential goods, rendering consumers in low-income countries more exposed to world market prices. We explore the consequences of this presumed differential substitutability between core and periphery as one building-block of our stress-test.

A second key hypothesis of dependency theorists relates more directly to the IO structure on which our stress-test is based. It follows the canonical definition of dos Santos (1970, p. 231) describing dependency as “a situation in which the economy of certain countries is conditioned by the development and expansion of another”. This definition focuses on the notion of asymmetry — the core affects the periphery much stronger than the other way round. We therefore conjecture that inflation spill-overs from the core to the periphery are quantitatively much more relevant than vice versa, in line with this oft-cited definition of dependency. Consequently, building on the core-periphery dichotomy enables us to uncover asymmetric shock trajectories and contrast heterogeneous vulnerabilities due to regional differences in price volatility and elasticities of substitution vis-à-vis non-EU-countries but also within the EU.

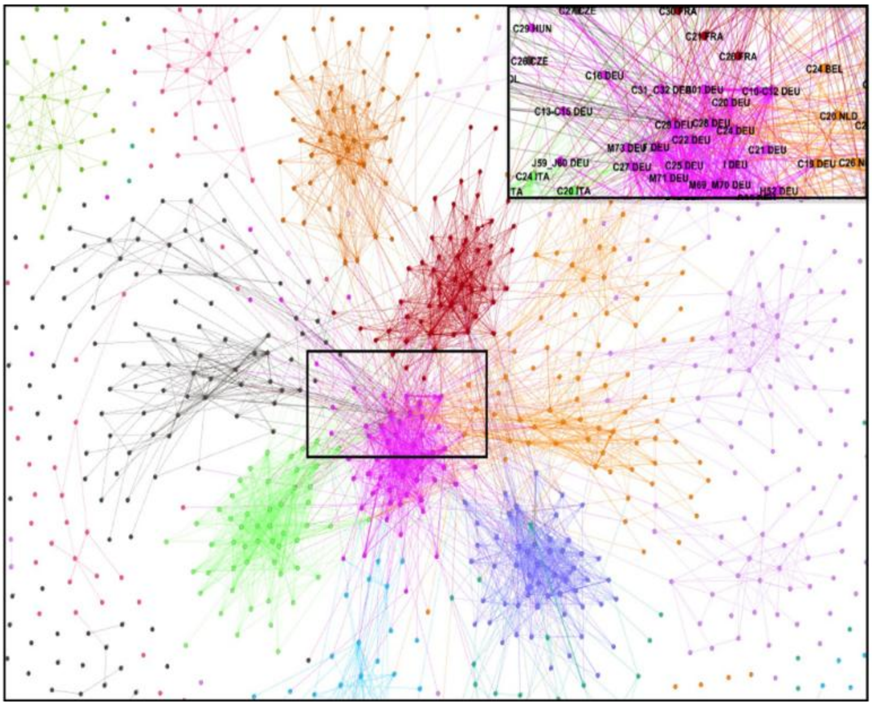

*Figure 1:* Snapshot of the EU production network in 2014 based on the World Input Output Database. Nodes (dots) represent sectors, edges (links) represent trade relationships of >385 million USD (smaller edges omitted for visibility reasons). Different colors indicate sectorial clusters of increased trade (identified using the Louvain method of community detection). Upper right panel magnifies the image detail, showing sector specifications according to ISIC Rev. 4. The network displays a clear core-periphery structure.

# 3. Data and methodology

For our empirical application, we use the World Input Output Database (WIOD). The WIOD provides annual panel IO data for the years 2000 until 2014, covering 43 countries with 56 sectors each, following the ISIC Rev. 4 classification (Timmer et al., 2015). These countries account for >85 percent of world GDP, offering an excellent representation of worldwide intermediate goods flows. The remainder of world economic activity is accounted for in a residual fictitious entity called “Rest of the World” (ROW). We use the most recent data from 2014 as a basis for the production network. Input price index data is taken from the WIOD’s Socio-Economic Accounts over the years 2000 – 2014 to calculate the price shocks in the model. The consumption shares are based on the values of final use for individual consumption in the EU, EU core, and periphery. We therefore allow for shock propagation of producer prices through worldwide supply chains, while focusing only on the implied CPI volatility for the respective European consumers.This contrasts with the approach within the paper by Weber et al. (2024a) who use national IO tables and consequently do not take shock transmission through global supply chains into account. A direct corollary to that is that Weber et al. likely underestimate the total impact of price shocks.

As for the model, we utilize the structure of the global production network to analyze the propagation of price shocks. Intuitively, different sectors are woven into a production network via their input and output linkages in their production processes of complex goods and services. IO models build on these inter-linkages by formulating a system of linear equations that describe the functional dependencies emerging from products flowing between sectors. Accordingly, these models can be used to analyze the propagation of shocks in this production network (Leontief, 1986; Miller and Blair, 2009). We build our stress-test exercise on the standard Leontief price model as has been used by Valadkhani and Mitchell (2002) and Weber et al. (2024a). The derivation of the IO price model can be found in Appendix A.

In our stress-test exercise, we expose every sector of our global production network to an individually empirically validated price shock. This shock in turn ripples through the production network, eventually reaching consumers' final consumption and therefore impacting the overall consumer price level. As in Weber et al. (2024a), we compute the individual shocks as the standard deviation of the yearly logarithmic price changes $\%\Delta P$ for every $\text{sector}_x$ in our observation period according to (1). We use price volatility since large price fluctuations impede predictability in economic decision-making and hence play a crucial role in the functioning of production networks and for household consumption (Damjanovic and Nolan, 2010).[5]

[5] We do check the robustness of our results for stress scenarios based on the mean price growth, as this is a another important aspect of price changes. Our results are not materially sensitive to this alternative specification.

$$\Delta P_x^{P_{t_0,t_1}} = \sqrt{\frac{1}{T}\sum_{t=t_0}^{t_1}\left(\%\Delta P_t^x - \%\Delta P_{t_0,t_1}^{\bar{x}}\right)^2} \quad (1)$$

Sectors experiencing more volatile price fluctuations will thus be exposed to a larger shock in our stress-test than relatively less volatile sectors. This approach considers the heterogeneous nature of price formations within different sectors.

As we show in Appendix A, the Leontief price model captures the following relationship

$$\Delta P_E = (I - A'_{EE})^{-1} A'_{XE}\, \Delta P_x \quad (2)$$

where $\Delta P_E$ measures the price volatility in the endogenous sectors induced by the price shock $\Delta P_x$ in the exogenous sector. In the next step, we introduce the sector-level shares of household consumption. We use three different sets of sector-level consumption shares corresponding to three different synthetic CPIs: one for the EU as a whole, one for the EU core countries and one for the EU periphery countries. Our categorization of core and periphery countries follows the standard definition within the literature (Gräbner et al., 2020a). While the classification by Gräbner et al. (2020a) is based on a multidimensional methodology, it is also consistent with our main argument grounded in differences of average incomes: the GDP per capita in each core country is higher than in each peripheral country, with the cut-off point being between Italy, with the lowest value in the core (34,460 USD per capita in 2010 dollars, as of 2014), and Malta (30,917 USD per capita) with the highest value in the periphery.[6]

[6] See Appendix B for a list with full country names. This categorization leaves us with a ratio of core to periphery sectors of 3:4. Where appropriate, we offset this imbalance by a normalization to facilitate comparability between regions. The procedure is detailed in Appendix C.

$c_{core}$ = {AUT, BEL, DNK, FIN, FRA, GER, GBR, ITA, IRL, LUX, NLD, SWE}

$c_{periphery}$ = {BGR, CYP, CZE, ESP, EST, GRE, HRV, HUN, LVA, LTU, MLT, POL, PRT, ROU, SVK, SVN}

Note that the consumption shares are the only variable that is varied for our analysis of the EU, EU core and periphery setup, respectively. The sector-level shocks as well as the links and weights of the global production networks remain the same for each of the three analyses. Per construction, differences in implied CPI volatility can only emerge from variation in consumption behavior between regions. Every disparity in the inflation exposure of EU, EU core and periphery is thus to be found in differences in the quantity and type of their consumption.

Having introduced the consumption shares, we are able to decompose (2) into

$$\pi^{direct} = c_x \Delta P_x \tag{3}$$

$$\pi^{indirect} = \sum_{i \neq x} c_i \; \Delta P_i \tag{4}$$

and

$$\pi^{total} = c_x \Delta P_x + \sum_{i \neq x} c_i \; \Delta P_i \; . \tag{5}$$

Equation (3) describes the volatility effect on the synthetic CPI that results from the price shock to final demand in the exogenously shocked sector. Equation (4) captures the higher-order propagation effects of this price shock due to the sector's IO linkages to other sectors and the affected final demand within these other sectors. Equation (5) finally gives us the total implied CPI volatility induced by the shock. If we sum over each equation, we get the direct, indirect and total price volatility in a region that was induced by our stress-test. Note, that the Leontief price model used for the stress-test assumes a 1:1 cost pass-through by each sector to either its customer sector or to final consumption. Therefore, the model overestimates price shock propagation where sectors find ways of substitution or function as a “price sink”.[7] While the issue of substitutability is a well-known limitation of (Leontief) IO models,[8] recent history has shown illustratively for the cases of semi-conductors and gas, that substitution can prove difficult in the short-run, which is the focus of our stress-testing exercise.[9] Backing this argument, research on firm-level cost pass-through suggests that firms completely pass-through sectoral cost shocks (Duprez and Magermann, 2018). Finally, a stress-test of inflationary exposure naturally aims to understand the upper bound of a potential adverse stress scenario. Accordingly, the Leontief price model seems to be an adequate choice to model cost-push stress scenarios on a sectoral level. Since pass-through is assumed and not calibrated, this exercise should not be interpreted as a prediction or reproduction of realized CPI volatilities, but as a stress-test used to identify and rank potential exposures to price volatilities following a stress scenario.

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[7] The estimation bias could in principle work also towards underestimation. Imagine for example sectors raising prices disproportionately compared to their risen input costs.

[8] Weber et al. (2024b) relax this assumption by extending their baseline model to capture conflict inflation in form of constant profit shares and constant real wages, respectively. Crucially, the systemic significance of sectors is not affected in either scenario. The simulations, however, point to important implications of the distributional consequences of cost-push shocks. Due to limitations of the dataset, we are unable to reproduce these additional simulations, since the WIOD does not provide data on nominal wages and profits for the “Rest of the World” category. However, Ipsen and Schulz (2024) as well as Schulz and Ipsen (2024) address distributional aspects of cost-push inflation based on a similar framework to Weber et al. (2024a) and the present paper.

[9] Even accounts like Bachmann et al. (2024) criticizing the assumptions of Leontief-type models acknowledge that substitution takes time and the elasticity of substitution is likely very low in the short run.

Figure 2 summarizes the hypothesized channels of our stress-testing exercise. Sectoral cost-push shocks affect the costs of final goods producers directly and in this way the synthetic CPIs via the consumption share vector. Since the input price index of a given sector also enters as input prices for other sectors, the production network amplifies the cost effect. In both regards, peripherality crucially mediates the effect: consumers in the periphery have lower income and thus cannot substitute away from especially volatile goods. Additionally, peripheral producers are also relatively more reliant on imports of intermediate goods, rendering them particularly vulnerable to volatility in global markets, i.e., the core and the rest of the world. Adding to Weber et al.'s (2024a) approach, we propose a formal operationalization of the concept of systemically significant prices for our dataset.[10] We take "systemically significant" to mean that the behavior of the aggregate ("system") is driven by a few "significant" components of the aggregate. To operationalize this concept, we leverage the properties of the power law distribution that governs the sectoral inflation impacts for all geographical disaggregations. While top observations might dominate aggregate statistics for other distributional forms (such as a log-normal distribution with high variance), this distributional functional form of a power law has the advantage that the inequality or concentration in the tail can be conveniently summarized by the tail exponent α. If this α is below two, the underlying distribution has infinite variance and continuing to sample from this population lets the sample variance increase without bounds. More pertinently, for such a distribution, the maximum sample observation almost entirely determines other summary statistics, especially its mean and, consequently, total value (Schulz and Milaković, 2023).[11] Thus, for a power law

[10] We employ the method of Clauset et al. (2009) to determine the minimal threshold of the power law distribution.

[11] To further illustrate this point, we conducted simulations for populations sampled from power laws with different tail exponents and calculated correlations between the sample mean and maximum values. For the empirically

distribution with a tail exponent below two, aggregates are indeed driven by the top "significant" observations.

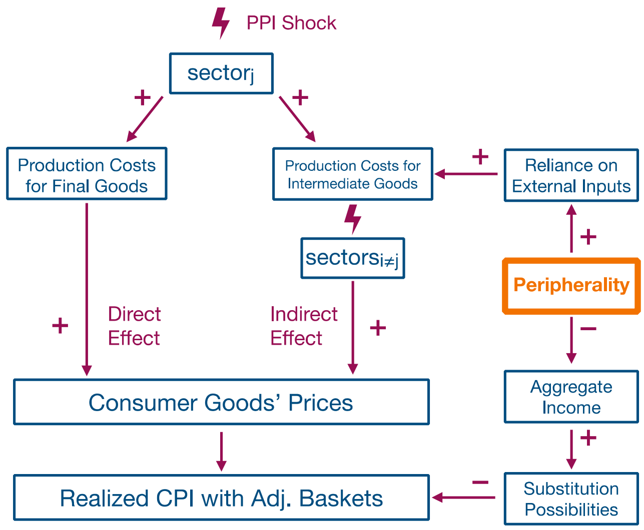


*Figure 2:* Exposure channels and mechanisms of our stress-test framework.

# 4. Results

Figure 3 documents the existence of systemically significant prices in the EU, EU core and periphery based on our power-law methodology.[12] It plots the sectoral ranks against the sector's total impact on aggregate CPI volatility with rank one showing the most impactful sector. All three regions display approximately linear behavior on a double-logarithmic scale, indicating that inflationary impacts are well described by a power law distribution. Estimating their tail exponents via maximum likelihood furthermore shows that all three spatial levels exhibit heavy upper tails with tail exponents below two and close to one: 1.10 (EU), 1.04 (EU core) and 1.00 (EU periphery). Therefore, we find that there indeed exist systemically significant prices across

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relevant parameter ranges, we find that there is almost a perfect correlation for all measures of association. The relevant simulation outcomes can be found in Appendix D.

[12] The code and a link to the publicly available data to reproduce the results of this paper can be found at https://github.com/ip5490/Stress-testing-Inflation-Exposure.

all considered regional disaggregations. The origins of this power law-like behavior are unclear, though. Typically, generating mechanisms build on a variant of stochastically multiplicative growth (Gabaix, 2009). For our case of inflationary impacts, this mechanism appears unlikely to be at play here.

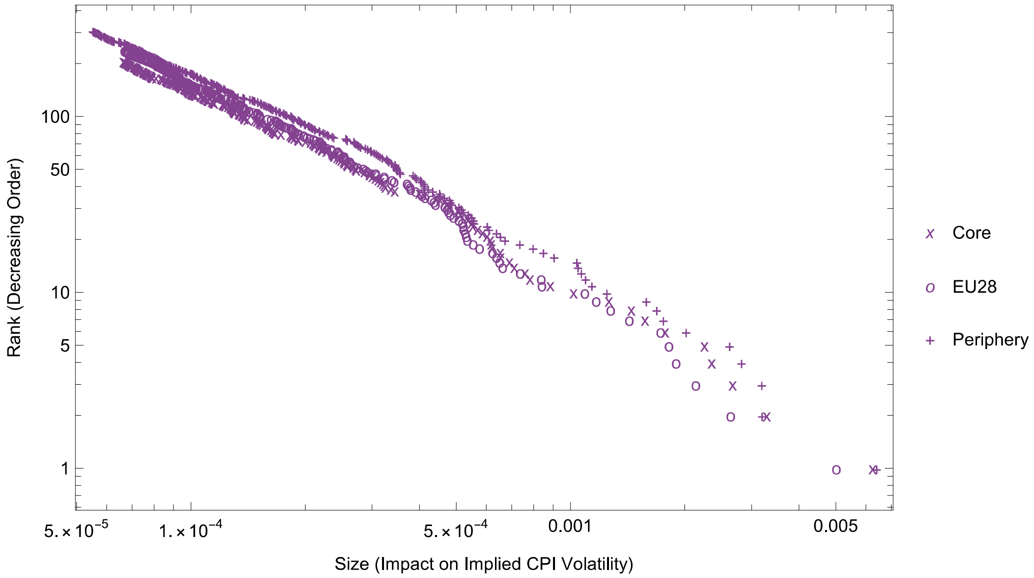


*Figure 3:* Rank of sectors according to their impact on implied CPI volatility in decreasing order against their impact on a double-logarithmic scale for three different regions. Threshold for the minimum of the power law determined by the method of Clauset et al. (2009). Approximately linear in behavior in all cases indicates power law upper tail.

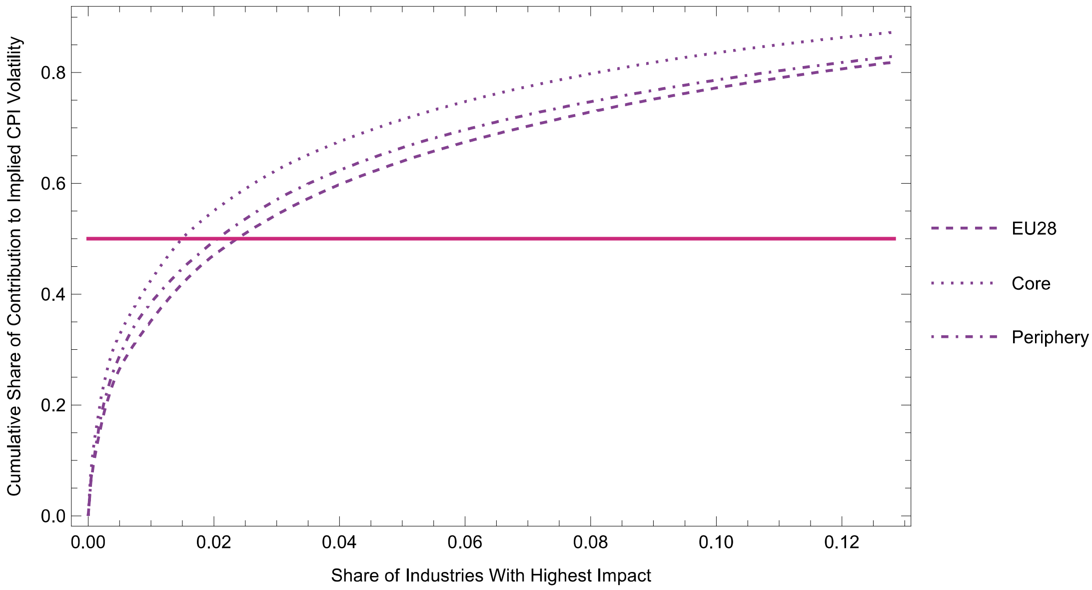


*Figure 4:* Share of industries needed to reach a certain cumulative impact on the consumer price level for EU, EU core and periphery specification, respectively. Horizontal line showing 50 percent threshold.

To gauge the highly asymmetric impact of different sectors apart from this distributional regularity, we plot the cumulative impact of these sectors in Figure 4. It shows the share of industries needed to reach a certain threshold of cumulative impact on the synthetic consumer price levels of each region. We see that in our model around two percent of industries with the highest impact account for 50 percent of the total contribution to CPI volatility in the EU28. Moreover, it shows that sectoral impacts in the core are even more asymmetric with fewer sectors driving the aggregate volatility of the synthetic CPIs compared to the periphery.[13]

Figures 5–7 take a closer look at the ten most significant sectors for the synthetic EU, EU core and periphery CPIs.[14] The bars can be read as: how much does the stress scenario (historical input price volatility) in $\text{sector}_j$ of $\text{country}_c$ affect the synthetic CPI of the EU, EU core and periphery? For the EU, sectors related to real estate activities, energy supply and production as well as financial services build the set of systemically significant prices. Comparing the EU core and periphery, there appear to be both structural similarities and differences in the composition and ranking of the most significant sectors. On the one hand, we find sectors of real estate activities, energy provision, financial services but also food manufacturing in both sets of systemically significant prices. On the other hand, there appear structural differences with the core being disproportionally affected by shocks in real estate activities while the

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[13] The attentive reader might wonder why, in Figure 4, the impact of core sectors is more asymmetric than for the peripheral sectors, even though the concentration within the power law tail in the periphery is higher (indicated by a lower estimated tail exponent). This is due to the fact that the gap in total impact between the power law and non-power law segments of the core estimates is higher than for the periphery, more than compensating for the higher concentration within the power law segment for the peripheral estimates.

[14] Appendix E provides tables including the effect sizes and sector-level average price volatilities that function as the stress scenarios.

periphery appears disproportionally exposed to sectors related to energy supply and production. Unsurprisingly, the respective largest economies constitute a disproportionate fraction of the set of systemically significant prices since the largest share of consumption happens within countries. Yet, in some cases, the list also reflects country-level idiosyncrasies driving up sectoral volatility. For example, the housing boom of the 2000s in the Netherlands increased the volatility of the Dutch real estate sector, even though the Dutch consumers only contribute little to overall consumption expenditures in the EU and the core countries. Similarly, the high volatility of the Polish manufacture of coke and refined petroleum sector reflects the geopolitical tensions and resulting price volatility of crude oil of this period.

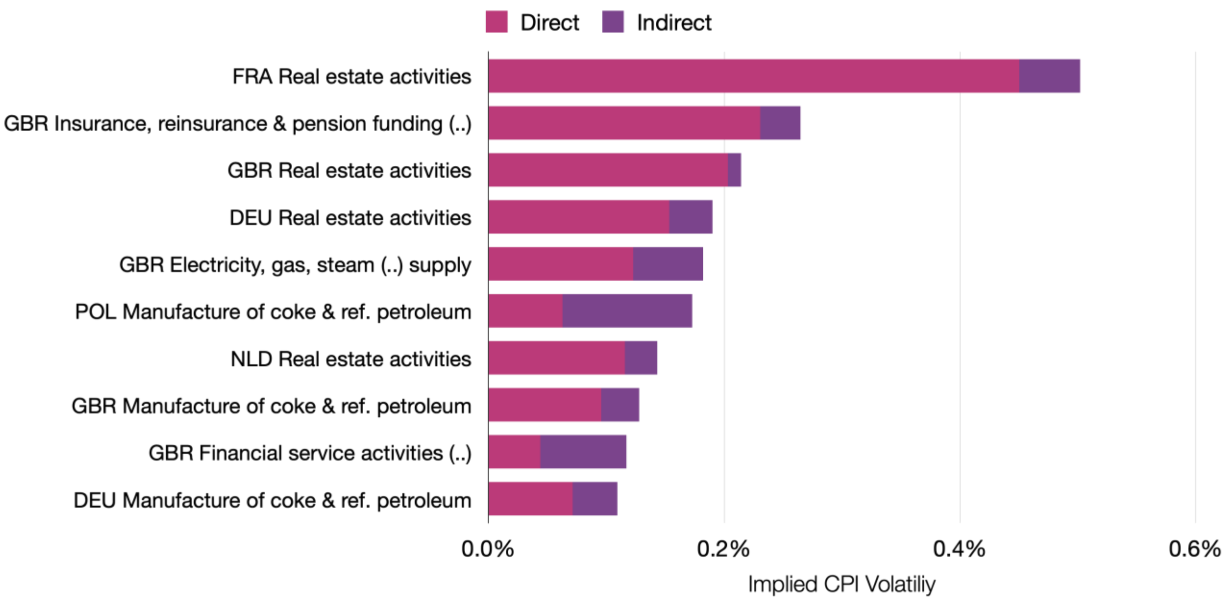


*Figure 5:* Implied CPI volatility induced by the ten most impactful national sectors for the EU (decreasing order). The total effect can be decomposed into the direct effect (magenta) on the synthetic CPI and the indirect effect (purple), i.e. the higher-order propagations.

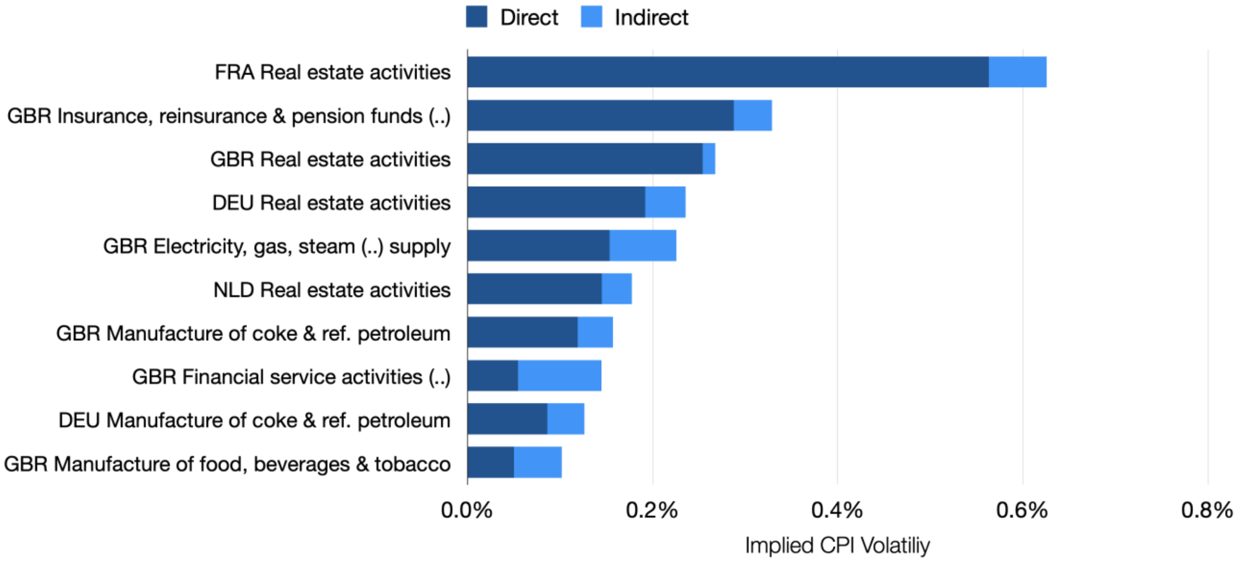


*Figure 6:* Implied CPI volatility induced by the ten most impactful national sectors for the EU core (decreasing order). The total effect can be decomposed into the direct effect (darker blue) on the synthetic CPI and the indirect effect (lighter blue), i.e. the higher-order propagations.

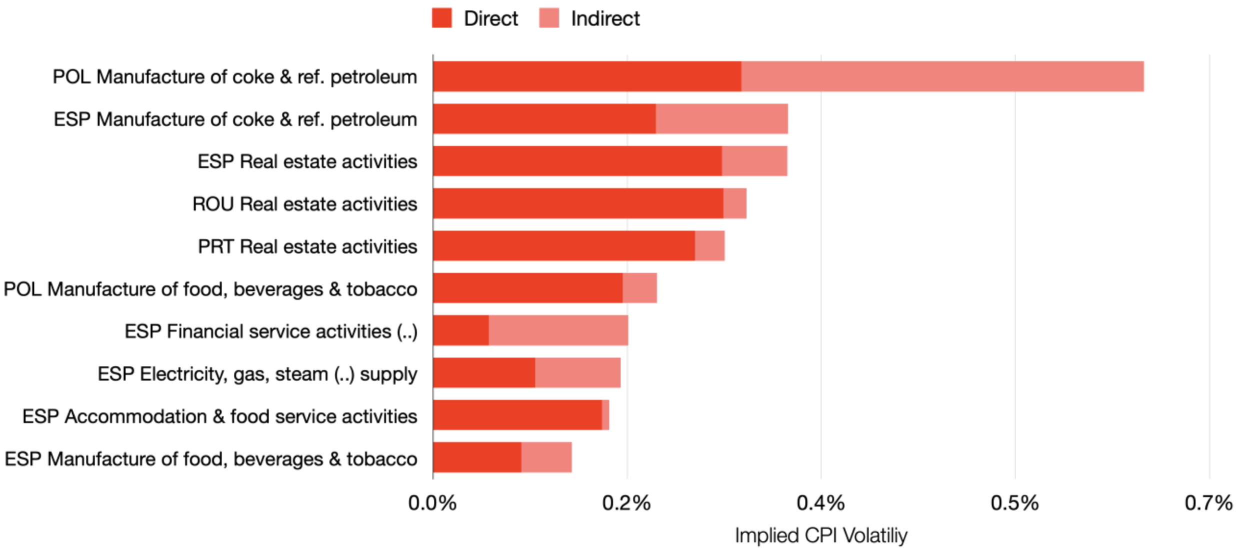


*Figure 7:* Implied CPI volatility induced by the ten most impactful national sectors for the EU periphery (decreasing order). The total effect can be decomposed into the direct effect (darker red) on the synthetic CPI and the indirect effect (lighter red), i.e. the higher-order propagations.

To better understand the structural similarities and differences between EU core and periphery, Figures 8–10 report the ten most important sector classes for the EU, EU core and periphery. These account for nearly 60 percent of implied CPI volatility in the respective regions. The bars give the sum of the direct and indirect CPI volatility in a region, induced by price shocks in a sector class.[15] The first bar in Figure 8 can be read as follows: if every "Real estate activities" sector in our dataset (one for each of the 43 countries in the WIOD) would experience its average price volatility, the implied CPI volatility impact for the EU consumers would be around 1.5 percent, with only a minor role for propagation effects (indirect effect). As such, it is ranked highest both in the EU and EU core. This picture changes for the synthetic CPI of EU periphery countries. Here, the sector of "Manufacturing of coke and refined petroleum products" is at the top. Naturally, the higher-order propagation effects for this sector class are substantially greater than for real estate activities.

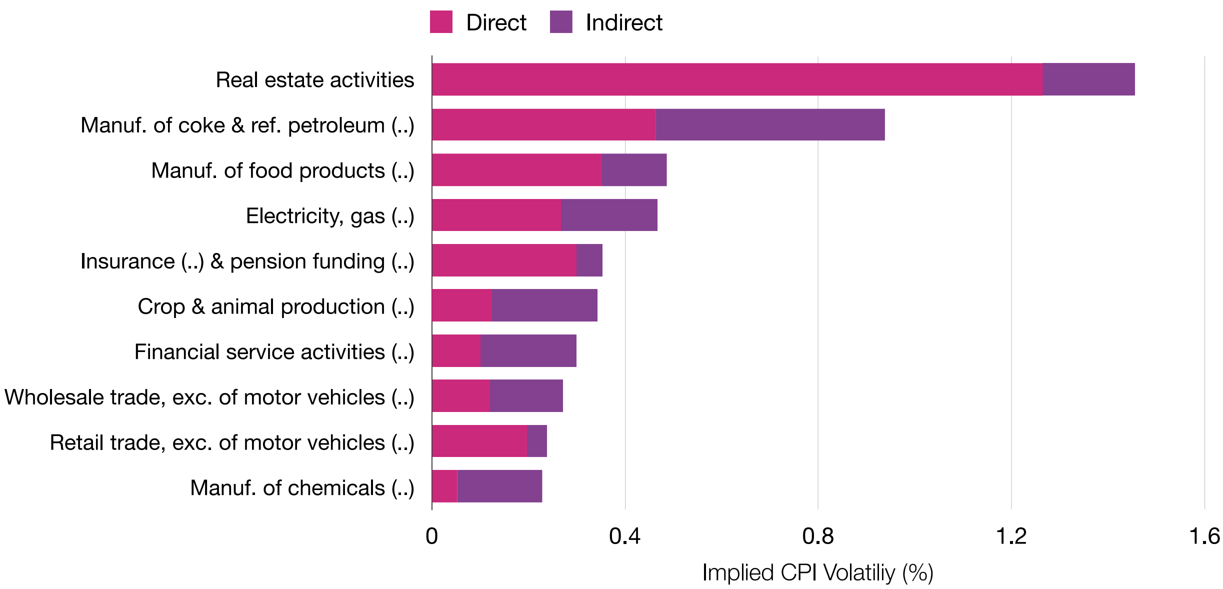


*Figure 8:* Summed CPI volatility induced by the ten most impactful sector classes for the EU (decreasing order). The total effect can be decomposed into the direct effect (magenta) on the CPI and the indirect effect (purple), i.e. the higher-order propagations.

[15] A sector class simply represents the set of every national sector in this class (sectorj in Brazil, France, Hungary, etc.). Therefore, each bar shows the implied CPI volatility in a region that emerges if every national sector of this class is shocked with its average price volatility.

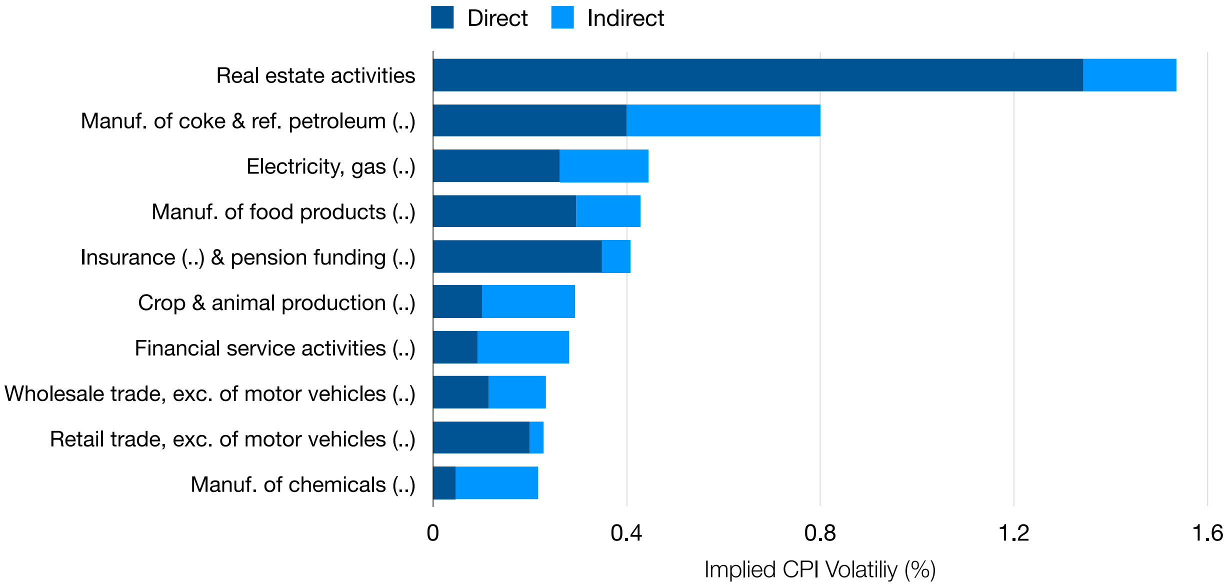


*Figure 9:* Summed CPI volatility induced by the ten most impactful sectors for the EU core (decreasing order). The total effect can be decomposed into the direct effect (darker blue) on the CPI and the indirect effect (lighter blue), i.e. the higher-order propagations.

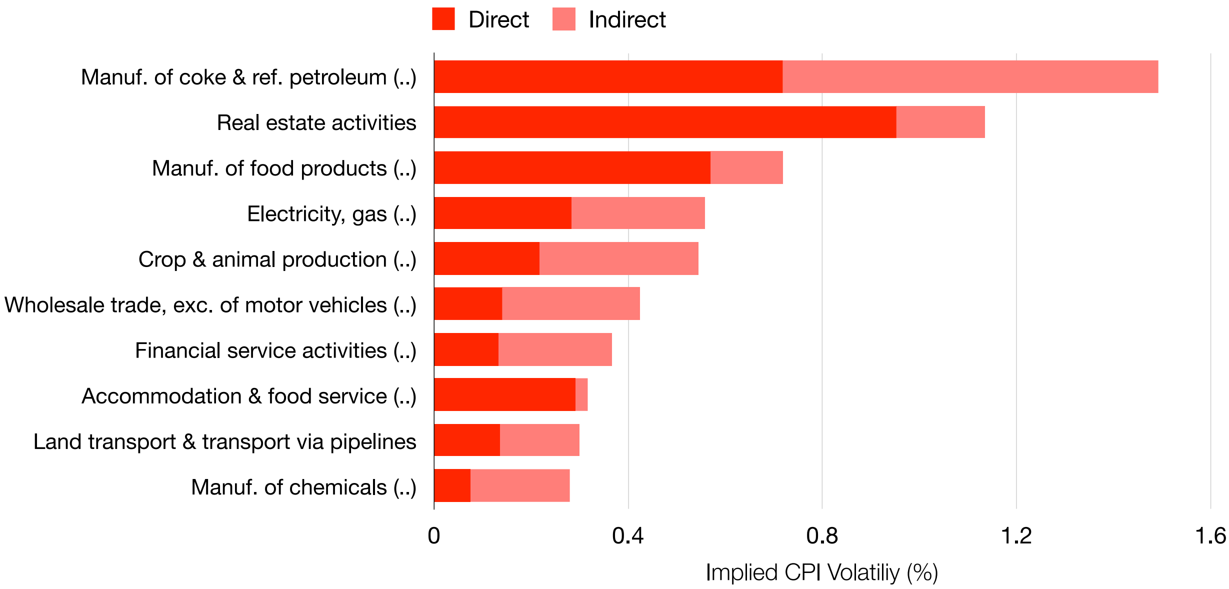


*Figure 10:* Summed CPI volatility induced by the ten most impactful sectors for the EU periphery (decreasing order). The total effect can be decomposed into the direct effect (darker red) on the CPI and the indirect effect (lighter red), i.e. the higher-order propagations.

Despite these differences, there again appear to be striking regularities in the set of systemically significant prices: the EU core and periphery share eight out of the ten most significant sector classes (though their relative importance differs).[16] In line with this observation, there exists a substantial overlap with the systemically significant prices identified by Weber et al. (2024a) for the United States[17] and, less surprisingly, also with the systemically significant prices for Germany (Weber et al., 2024b)[18] and France (Goldztejn, 2024)[19].

In general, the classes of real estate activities, food production as well as raw materials in the form of energy supply appear as systemically significant across all extant studies. Real estate sectors mostly matter because of their direct impact, while the sectors qualifying as energy suppliers also matter through their indirect effect, i.e., their pivotal role for other sectors in the production process (Usman et al., 2024). These results indicate that either size, understood as share in total consumption, or centrality in the form of supplying essential (agriculture) or

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[16] These are "Real estate activities", "Manufacturing of coke and refined petroleum products", "Manufacturing of food products", "Electricity, gas, steam and air conditioning supply", "Crop and animal production, hunting and related service activities", "Wholesale trade, except of motor vehicles and motorcycles", "Financial service activities, except insurance and pension funding", "Manufacture of chemicals and chemical products".

[17] These are "Petroleum and coal products," "Oil and gas extraction," "Farms," "Food and beverage and tobacco products," "Chemical products," "Housing," "Utilities," and "Wholesale trade" (Weber et al., 2024a). While, due to differences in the classification, a one-to-one mapping to our results is not possible, the significant overlap is nevertheless apparent.

[18] The ten most important sectors (as of 2019) are identified to be: "Electricity, Heating and Cooling", "Land Transport", "Freelance and Other Services", "Food, Beverages and Tobacco", "Warehousing", "Coke and Petroleum Products", "Other Economic Services", "Agriculture", "Real Estate Services" and "Oil and Gas" (Weber et al., 2024b).

[19] These are "Coking and refining", "Real Estate Activities", "Trade", "Manufacture of food, beverages and tobacco products", "Agriculture, forestry and fisheries", "Finance and Insurance Activities", "Production and distribution of electricity, gas, steam and air conditioning", "Telecommunications", "Transport and storage", "Legal, accounting, management, architecture, engineering, control and technical analysis activities". While again, a one-to-one mapping to our results is not possible, the significant overlap is apparent.

universal (energy) inputs may render a sector systemically significant, rather than merely considering its unweighted volatility itself.

Tables 1 and 2 further decompose the geographical asymmetries in price volatility in the EU periphery vis-à-vis the core: while the EU core experiences 4.40 percentage points of direct and 3.41 percentage points of indirect effects, accumulating to 7.81 percentage points in total, the periphery is exposed to 5.35 percentage points of direct and 4.64 percentage points of indirect effects, accumulating to 9.99 percentage points.

| Effects | Core to Core (%) | Periphery to Core (%) | non-EU to Core (%) | Sum (%) |
|---|---|---|---|---|
| direct | 4.13 | 0.11 | 0.16 | 4.40 |
| indirect | 2.51 | 0.26 | 0.64 | 3.41 |
| total | 6.64 | 0.37 | 0.80 | 7.81 |

*Table 1:* Inflation exposure in percentage points for the core vis-à-vis core, periphery and non-EU countries. Decomposed into direct, indirect and total effect. Consider, for example, the first cell in the first row: The direct effect of shocks diffusing from core sectors accounts for 4.13 percentage points of inflation impact in the core. The ratio of sectors in the core and peripheral countries are normalized to a 1:1 ratio to prevent under-/overestimation by differing numbers of sectors.

| Effects | Periphery to Periphery (%) | Core to Periphery (%) | non-EU to Periphery (%) | Sum (%) |
|---|---|---|---|---|
| direct | 4.80 | 0.37 | 0.18 | 5.35 |
| indirect | 2.88 | 0.92 | 0.84 | 4.64 |
| total | 7.68 | 1.29 | 1.02 | 9.99 |

*Table 2:* Inflation exposure in percentage points for the periphery vis-à-vis core, periphery and non-EU countries. Decomposed into direct, indirect and total effect.

Therefore, the indirect effect makes up a higher share of the total inflation exposure for peripheral countries compared to the core. Considering the volatile price formation in raw material sectors, the difference in the importance of raw materials between EU core and periphery at least partially explains the greater volatility in the periphery. According to Herman Daly's 'inverted pyramid', this higher volatility stems from the position of raw materials and energy at the outset of the production process (Cahen-Fourot et al., 2020).

A greater dependence on raw materials naturally suggests a more exposed position in world markets. We see this hypothesis confirmed when illustrating the price shock trajectories (Figure 11). The EU periphery imports 1.02 percentage points of its inflation exposure from sectors located in countries outside the EU, while it is only 0.80 percentage points for the EU core. In addition to that, peripheral countries also bear a greater inflation exposure vis-à-vis core countries. While core countries face an exposure of only 0.37 percentage points from peripheral countries, price volatility diffusing from core sectors to the periphery is more than three times this size (1.29 percentage points). Conversely, while it is the upstream sectors of raw materials exposing peripheral countries to price volatility, it is the higher dependence on down-stream sectors such as real estate activities that seem to prevent the EU core from importing a similar share of volatility. These findings, based on a very different dataset, are in line with results from Joya and Rougier (2019) and Chakraborty et al. (2024), who find lower-income countries to be more exposed to supply-chain risk from outside their region compared to higher-income countries.

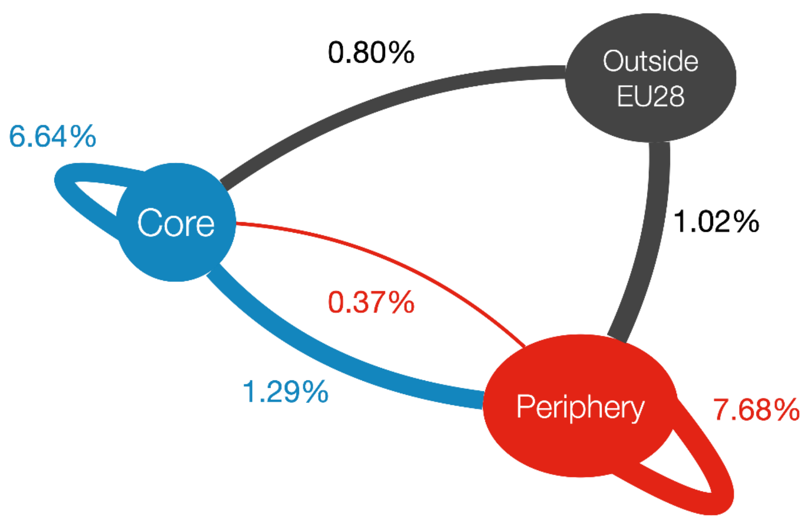


*Figure 11:* Paths of price volatilities originating in EU core, periphery and outside EU28 countries, respectively.

The results from recovering consumption substitution effects (6) shed more light on the asymmetric inflation exposure.[20] Consumers in the peripheral countries seem to be at the mercy of price volatilities, while consumers in the core countries are better able to substitute away from increasingly volatile prices. More formally, the cross-sectional covariance between consumption shares and price volatilities is virtually non-existent for the periphery (0.05 percentage points), while it is significantly negative for the core (−0.89 percentage points). The mean price volatility $\bar{\pi}$ is 5.3 percentage points.

$$\pi^{direct} = \bar{\pi} + (N-1) \cdot cov(c_x, \Delta P_x) \qquad (6)$$

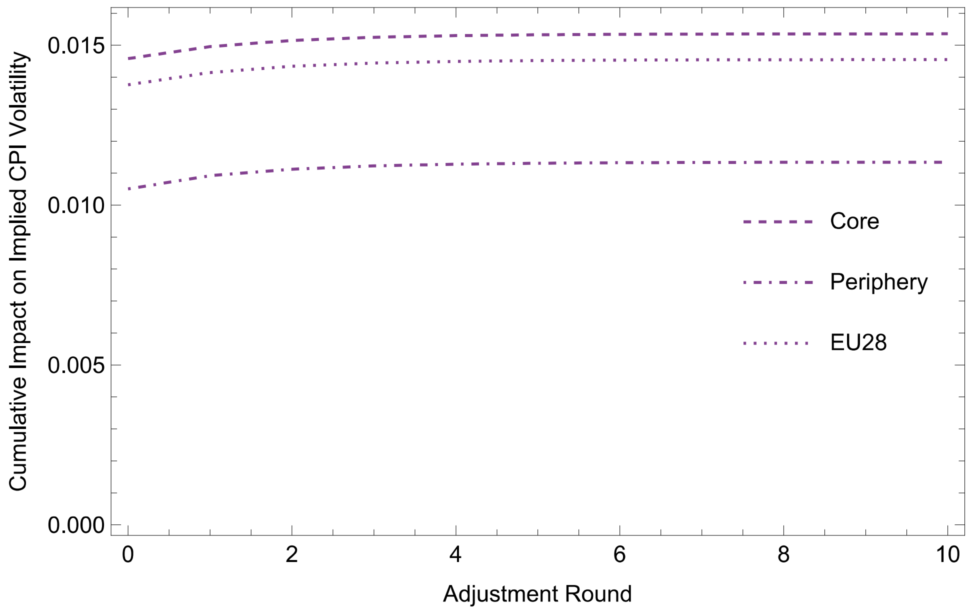


*Figure 12:* Round-to-round approximation for "Real Estate Activities". Round 0 shows the direct effect. Round 1 to 10 showing the cumulative indirect effects adding to round 0 (decimal values).

[20] This decomposition holds, since consumption shares c sum to one (Olley and Pakes, 1996).

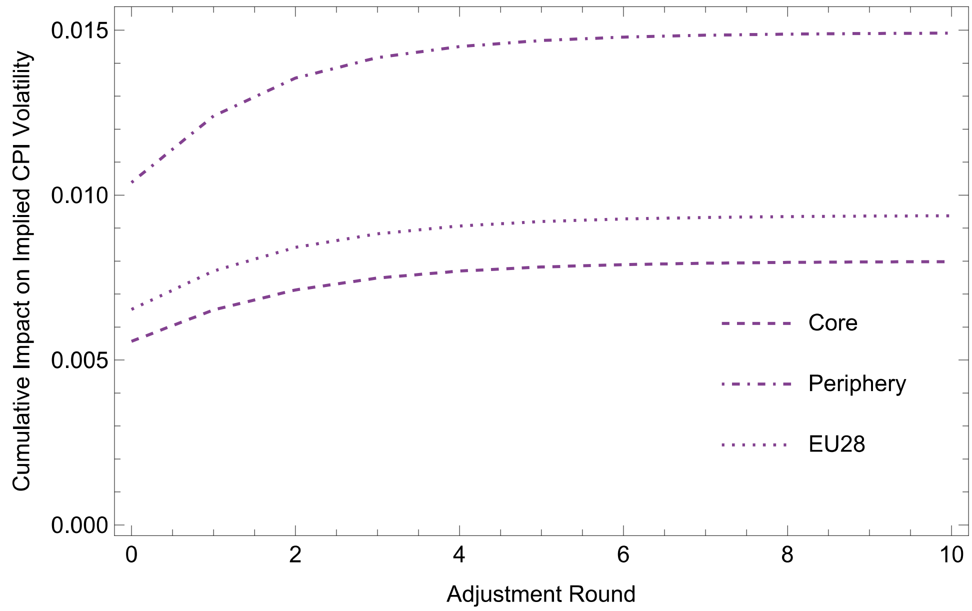


*Figure 13:* Round-to-round approximation for "Manufacturing of Coke and Refined Petroleum". Round 0 shows the direct effect. Round 1 to 10 showing the cumulative indirect effects adding to round 0 (decimal values).

Finally, Figures 12 and 13 show the round-to-round decomposition for the two most relevant cases of the sector classes "Real Estate Activities" (top) and "Manufacturing of Coke and Refined Petroleum" (bottom), respectively. Round 0 marks the direct effect a sector causes when confronted with our stress scenario. Rounds 1 to 10 show the cumulative indirect effects adding to the direct effect of round 0. We see that there exist sizable intersectoral and geographical differences in the round-to-round effects. The decomposition also shows the bulk of higher-order effects to be limited to the first five to six rounds. This implies that price shocks mostly diffuse within a small number of sectors and thus display rather short path-lengths.

These results are valuable in and of itself, however, also shield our analysis against the critique of Leontief IO models unrealistically considering an infinite number of adjustment rounds, or, equivalently, that all adjustments happen instantaneously neglecting historical time in the basic model mechanism (for a related criticism of comparative statics and historical time, cf. Robinson, 1980).

Overall, peripheral countries seem to be confronted with a significantly greater inflation exposure due to their greater reliance on raw materials and dependence on core and outside-EU sectors. Part of this exposure is attributable to differences in the production regime. However, and in line with the reasoning of Pasinetti (1983), we show that a substantial share of exposure stems from differences in the ability to substitute away from volatile sectors

# 5. Discussion

As key inflation propagators, the identified systemically significant prices present risks that need to be addressed by administrations of national and supranational levels. Our simulation results suggest that about two percent of sectors generate more than half of the total inflation exposure. Weber and Wasner (2023) and in more detail van't Klooster and Weber (2024) discuss several levers to decrease and manage exposure against systemically significant prices and cost-push inflation more generally: First, improving the monitoring of exposures, which hinges on the quality, granularity and timeliness of available data, is a key aspect of preparing for future stress scenarios. The recent upheavals caused by semi-conductor shortages have shown that the identification of systemically significant prices should not stop at the sectoral level but needs to examine the firm- and product-level as well. Second, improved competition policy might reduce pass-through in sectors that profit from (temporary) bottlenecks. Third, the implementation of buffer stocks for systemically significant prices – in analogy to the Basel III framework for banks that also includes stress-testing – could not only decrease pressure on prices in times of stress but go well beyond by ensuring production and supply of essentials. Furthermore, the authors discuss the taxation of windfall profits and strategic price controls as potential measures. Baldwin and Freeman (2022) articulate similar considerations, including supply diversification and reshoring, and emphasize the role of public regulatory responsibility in cases where public harm needs to be prevented. Our results show that this discussion also needs to consider the asymmetric exposures faced within the EU, with the EU periphery being subject to a set of key constraints. Naturally, the exposure of peripheral countries is linked to their lower average income, which in turn limits their capability for consumption substitution. This points to an appropriate fiscal transfer scheme on the national (and supranational) level, but also to targeted regional development strategies to facilitate European cohesion. These should not only take the path-dependent nature of economic development into account (Deegan et al., 2021), but also aim to reduce exposure. Next, we find that peripheral price volatility depends strongly on the core and the rest of the world. This means that policymakers in the peripheral countries are less capable of controlling these largely external sources of disturbances. Building technological capabilities, especially in renewable energies, could reduce their dependence on volatile imports of fossil fuels and hence decrease inflation exposure. A final challenge for mitigation policies are differences in the sectoral composition, that drive the response to cost-push shocks. We find the total impact of industries to be more concentrated in the core compared to the periphery. Thus, policy and costly supervision in the periphery needs to cover more sectors. Qualitatively, the most significant drivers of inflation exposure in the core are the various real estate sectors, while it is sectors related to energy production and raw materials in the periphery. Since monetary policy is highly asymmetric in its impact both on the regional and the sectoral level, a common monetary policy as in the Eurozone might therefore cause further divergence of core and periphery (Beraja et al., 2018; Carlino and DeFina, 1998; Peersman and Smets, 2005). In particular, there exists evidence that monetary policy is more effective in curbing the price volatility of residential investment (Enders and Ma, 2011). Given that the real estate sector dominates the synthetic CPI of the core but only to a lesser extent the synthetic CPI of the periphery, monetary policy might thus only further the volatility differential between core and peripheral countries, calling for counteracting fiscal measures both on the national and supranational level.

# 6. Conclusion

Our paper provided a stress-test for inflation exposure explicitly accounting for amplification in production networks. Applying data from the World Input Output Database to a Leontief price model, we confirmed the existence of systemically significant sectors for synthetic CPIs of the EU, EU periphery and core. Adding to Weber et al. (2024a), we suggest a new approach to operationalize the existence of systemically significant prices based on the mathematical properties of power law distributions. Documenting several dimensions of sectoral and spatial heterogeneity, we hope to aid policy to enhance European inflation resilience by highlighting potential levers for which targeted policies could disproportionately affect aggregate outcomes. Theoretically, our results imply that the notion of inflation as a purely aggregate phenomenon underlying much of orthodox macroeconomics is too simplistic and ignores the role of systemically significant prices and shock propagation within production networks. Yet, our simulation also has several limitations, essentially due to the lack of more current and granular data: The data does not cover the most recent period of high inflation and is highly aggregated on a country level. Since we do not have consumption microdata, we implicitly employ the fiction of a representative consumer for a region and only consider shares in the total consumption of said region. This prevents us from examining the effects of cost-push shocks along the personal income distribution, which are arguably even more important for policy (see Schulz and Ipsen, 2024). Also, as Weber and Schulz (2025) show, core-periphery patterns are more prevalent on the much more granular county level, which, with the appropriate data, calls for an even more granular study of the spatial propagation of cost-push shocks. Finally, the Leontief price model implicitly makes strong assumptions about substitutability along the supply chain, rendering our simulation results upper-bound estimates. We aim to address these issues in further research, investigating country-specifics as a first step, and augment our propagation model with a modified Leontief production function that partially allows for input substitution (Pichler et al., 2022). Notwithstanding these limitations, our paper provides a first stress-test for inflation exposure in supply chains that takes spatial heterogeneities seriously and can be straightforwardly applied and extended to other scenarios.

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# Appendix A: Input-output Price Model

To stress-test inflation exposure, we set up a standard IO model as has been used by Valadkhani and Mitchell (2002) or Weber et al. (2024). IO models build on the inter-linkages between sectors by formulating a system of linear equations that describe the functional dependencies emerging from products flowing between sectors and can thus be used to analyse the propagation of shocks in this production network (Leontief, 1986; Miller and Blair, 2009). In our case the model allows us to simulate the impact of a price shock in a given sector on the overall price level. The following will see the derivation of the basic Leontief price model used for our stress-test exercise.

In an economy, the value of sector$_j$ output can be understood as the quantity $x_j$ times the price $P_j$ of sector$_j$ output. As seen in (i), $x_jP_j$ can be decomposed into a) a multiplicative combination of $x_j$, the technical coefficient $a_{ij}$, which is the ratio of value of inputs from sector$_i$ to the overall value of sector$_j$ output, and the price of sector$_i$ output, plus b) the Value Added of sector$_j$.[21]

$$x_j\,P_j = x_j\,a_{1j}\,P_1 + \cdots + x_j\,a_{ij}\,P_i + \cdots + x_j\,a_{nj}\,P_n + V_j \qquad \text{(i)}$$

While IO tables do not disentangle quantities and prices but display their product i.e. production values in currency units, IO tables make do by normalizing the output of each sector so that its unit price is equal to one. This allows us to shock one sector and observe the results of the induced price formation process as percentage changes in each sector's prices (Miller and Blair, 2009; Weber et al., 2024).

Introducing $n$ sectors yields a system of linear equations that governs their IO relations. The matrix representation of this system can be expressed as

[21] Note that we neglect imports in this setup, as we are working with global data and thus already cover imports within a).

$$\hat{X}\,P = \hat{X}\,A'P\ + V \qquad \text{(ii)}$$

with $\hat{X}$ as the diagonal matrix of the sector's total output, *P* as a vector of prices, *A* as the matrix of technical coefficients and *V* as the vector of value added. Dividing by the total output matrix $\hat{X}$ yields the price per unit of output

$$P = A'\,P + v \qquad \text{(iii)}$$

and finally solving for *P* gives

$$P = (I - A'\,)^{-1}\,v \qquad \text{(iv)}$$

With $(I - A')^{-1}$ as the Leontief Price Inverse. Fixing the technical coefficients, that is, the ratio of value of inputs of $\text{sector}_j$ to the value of outputs of $\text{sector}_i$, allows the model to now determine prices endogenously. This setup allows us to simulate cost-push inflation via price shocks to a given sector.

Note that the fixed technical coefficients imply full cost pass-through and no possibilities of substitution. Thus, the model overestimates price shock propagation where sectors find ways of substitution or function as a "price sink".[22] The same holds for wages, which, as a consequence of the fixed technical coefficients, also remain constant in nominal terms. In this exercise, we aim isolate the short-term effect of a cost-push channel and therefore do not take

[22] The estimation bias could in principle work also towards underestimation. Imagine for example sectors raising prices disproportionately compared to their risen input costs. However, it is arguably reasonable to assume the overestimation bias dominates these conflicting effects.

the effects on the functional distribution of income and potential feedback mechanisms between price determination and distribution into account.[23]

Albeit the issue of substitutability being a well-known limitation of IO models, they do not carry as much weight in our implementation as a stress-test of inflationary exposure, since we are interested in understanding the upper bound of potential adverse shocks. Additionally, recent history has shown illustrative for the cases of semi-conductors and gas, that substitution can prove difficult in the short-run, which is the focus of our stress-testing exercise.

Following Valadkhani and Mitchell (2002) and Weber et al. (2024), we simulate a price shock to a sector by setting the respective sector exogenous which allows us to solve the system of equations for the inflation impact of a specific producer price shock (see also Miller and Blair (2009) for a detailed account on this process). Effectively, this allows us to set the price for a particular sector$_j$ and observe how this price shock propagates to and within the endogenous price formation process of all sectors $i \neq j$. Note that there will be no feedback from the endogenous part of the model to the sector that is set exogenous. Ruling out changes in the quantities of inputs for the endogenous sectors, this process transforms (iv) to

$$P_E = (I - A'_{EE})^{-1} A'_{XE} P_X \tag{v}$$

with $P_E$ and $P_X$ as the price vectors of the endogenous and exogenous sectors, respectively. Thus, the impact of a price shock is conditional on the level of the shock $P_X$ as well as the nature of the IO network realized in $(I - A'_{EE})^{-1}$ and $A'_{XE}$. The latter is an $e \times x$ matrix, containing the direct input requirements of the endogenous industries from the exogenous industries, while $A'_{EE}$ is an $e \times e$ matrix containing the direct input requirements of endogenous industries from endogenous industries.

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[23] See Weber et al. (2022) and Weber and Wasner (2023) for a discussion of these aspects.

# Appendix B: Country Names

AUT : Austria

BEL : Belgium

BGR : Bulgaria

CYP : Cyprus

CZE : Czech Republic

DNK : Denmark

ESP : Spain

EST : Estonia

FIN : Finland

FRA : France

GBR : Great Britain

GER : Germany

GRE : Greece

HRV : Croatia

HUN : Hungary

ITA : Italy

IRL : Ireland

LTU : Lithuania

LUX : Luxembourg

LVA : Latvia

MLT : Malta

NLD : Netherlands

POL : Poland

PRT : Portugal

ROU : Romania

SVK : Slovakia

SVN : Slovenia

SWE : Sweden

# Appendix C: Normalization

One issues that arises immediately for comparing the estimates of our model between core and periphery is that there are more core than peripheral sectors and the total effects are thus not directly comparable. To remedy this, we use a simple correction method:

1) Let $e_i$ be the uncorrected inflation impact of region$_i$ that is a subset of all regions, i.e., $i$ can refer to the core, periphery or rest of the world. Determine the uncorrected share of region$_i$ : $s_i \frac{e_i}{\sum_j e_j}$ .
2) Determine the share of the amount of sectors in $i$ compared to the whole sample. Divide $s_i$ by this share: $\widetilde{s_i} = \frac{s_i}{\#i/\sum_j \#j}$ , with # as the number of elements in a set. If $\widetilde{s_i}$ is above unity, then the inflation effect of $i$ is higher than would be expected by the number of sectors it entails and vice versa.
3) Correct the share by $\widehat{s_i} = \frac{\widetilde{s_i}}{\sum_j \widetilde{s_i}}$ .
4) Multiply by the total effect of all regions to get a corrected estimate while preserving the total inflation impact: $\widehat{e_i} = \widehat{s_i} \cdot \sum_j e_j$.

# Appendix D: Stress-test Scenarios

| Country & Sector Name | Mean Price Volatility (%) | Implied CPI Volatility (%) |
|---|---|---|
| FRA Real estate activities | 13.83 | 0.50 |
| GBR Insurance, reinsurance & pension funds (..) | 22.59 | 0.26 |
| GBR Real estate activities | 5.03 | 0.21 |
| DEU Real estate activities | 4.31 | 0.19 |
| GBR Electricity, gas, steam (..) supply | 21.44 | 0.18 |
| POL Manufacture of coke & ref. petroleum | 80.17 | 0.17 |
| NLD Real estate activities | 17.45 | 0.14 |
| GBR Manufacture of coke & ref. petroleum | 38.64 | 0.13 |
| GBR Financial service activities (..) | 8.28 | 0.12 |
| DEU Manufacture of coke & ref. petroleum | 16.81 | 0.11 |

*Table D1:* Mean price volatility shock for ten most impactful sectors in EU specification.

| Country & Sector Name | Mean Price Volatility (%) | Implied CPI Volatility (%) |
|---|---|---|
| FRA Real estate activities | 13.83 | 0.63 |
| GBR Insurance, reinsurance & pension funds (..) | 22.59 | 0.33 |
| GBR Real estate activities | 5.03 | 0.27 |
| DEU Real estate activities | 4.31 | 0.24 |
| GBR Electricity, gas, steam (..) supply | 21.44 | 0.23 |
| NLD Real estate activities | 17.45 | 0.18 |
| GBR Manufacture of coke & ref. petroleum | 38.64 | 0.16 |
| GBR Financial service activities (..) | 8.28 | 0.14 |
| DEU Manufacture of coke & ref. petroleum | 16.81 | 0.13 |
| GBR Manufacture of food, beverages & tobacco | 8.62 | 0.10 |

*Table D2:* Mean price volatility shock for ten most impactful sectors in EU core specification.

| Country & Sector Name | Mean Price Volatility (%) | Implied CPI Volatility (%) |
|---|---|---|
| POL Manufacture of coke & ref. petroleum | 80.17 | 0.64 |
| ESP Manufacture of coke & ref. petroleum | 29.33 | 0.32 |
| ESP Real estate activities | 3.91 | 0.32 |
| ROU Real estate activities | 29.15 | 0.28 |
| PRT Real estate activities | 20.70 | 0.26 |
| POL Manufacture of food, beverages & tobacco | 9.44 | 0.20 |
| ESP Financial service activities (..) | 11.32 | 0.18 |
| ESP Electricity, gas, steam (..) supply | 7.35 | 0.17 |
| ESP Accommodation & food service activities | 2.17 | 0.16 |
| ESP Manufacture of food, beverages & tobacco | 2.82 | 0.12 |

*Table D3:* Mean price volatility shock for ten most impactful sectors in EU periphery specification.

# Paper 3

# Investigating the Impact of Climate-Related Risks: A Regime-Switching Analysis of Bond Market Dynamics and Inflation Expectations

**Publication status and bibliographic information**

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**Abstract**

We examine how climate-related transition and physical risks impact European bond markets and inflation expectations and identify their effects across distinct volatility regimes using a Markov-switching vector autoregression model. Our central finding is that the transmission of climate-related risk shocks is highly state-dependent and primarily affects short-term inflation expectations. Transition risks have a limited, disinflationary effect on short-term expectations, but only during low-volatility periods. In sharp contrast, physical risks exert a destabilising, inflationary impact during high-volatility periods, depressing bond returns and amplifying market stress. Additionally, we observe two further patterns. First, long-term inflation expectations tend to remain largely anchored. Second, financial linkages and contagion tend to intensify in the high-volatility state. Our findings matter for asset pricing and for monetary authorities. They support integrating climate-related risks into stability frameworks, as these shocks presumably intensify and complicate the trade-off between inflation-target credibility and financial stability.

**Author's contribution**

Rafael Kothe and I conceptualized the study together, collected the data, and conducted extensive preliminary analyses. Convinced that accounting for volatility regimes was essential, we invited Lisa Sheenan, an expert in the field, to lead the regime-switching analyses. Rafael Kothe and I jointly took responsibility for all the remaining writing and organizational tasks.

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# 1 Introduction

As a global leader in climate regulation and sustainable finance, Europe is at the forefront of confronting the financial implications of climate transition policies and environmental shocks. These risks, broadly classified into transition risks arising from regulatory and technological shifts toward a low-carbon economy and physical risks stemming from climate-induced disruptions, pose growing challenges for asset valuation, monetary policy, and market stability. In particular, concerns have emerged over how such risks interact with inflation expectations and bond pricing mechanisms in Europe's integrated financial markets, particularly under volatile conditions (Battiston et al., 2021; Boissay et al., 2023). Additionally, concerns regarding financial stability have emerged due to these climate-related risk-induced cost-push inflationary dynamics (Ciccarelli et al., 2023; Jackson, 2024). Indeed, in recent years, central banks have begun to identify the green transition and physical climate change as sources of financial stability risk (Battiston et al., 2021).

If these pressures become more structural, they could amplify the trade-off between monetary policy and financial stability for central banks.[1] It is understood that climate change and related policies may trigger macroeconomic and financial instability by impairing the balance sheets of firms, households, banks, and insurers. Delayed or abrupt transitions may amplify risks, either through intensified physical damage or sudden reallocations of capital (Batten et al., 2016; European Systemic Risk Board, 2016). Alongside these macroprudential considerations, the evolving landscape of climate-related risks presents significant challenges and opportunities for risk management and portfolio construction (Bertolotti, 2020). Understanding how these risks manifest in European financial markets, particularly across different asset classes and volatility regimes, is crucial for institutional investors seeking to optimise risk-adjusted returns and build resilient portfolios (Krueger et al., 2020).

While the literature has explored the effects of climate-related risks on equity markets, commodity prices, and credit risk premia (Cepni et al., 2023; Krueger et al., 2020), and identified multiple transmission channels with emphasis on nonlinearities (Battiston et al.,

[1] See, e.g., Boissay et al. (2023); Chavleishvili et al. (2023) for detailed mechanisms.

2021, 2017; Semieniuk et al., 2021; Stolbova et al., 2018), relatively little is known about how these risks influence market-based inflation expectations and bond returns across different volatility regimes. This puzzle remains under-investigated, despite its growing policy relevance for the euro area.

To address this gap, we examine how news-based measures of transition and physical climate risks transmit to inflation expectations and bond markets in Europe, with particular attention to regime-dependent dynamics during periods of financial stress. We employ a Markov-switching Vector Autoregression (MS-VAR) combined with the news-based Transition Risk Index (TRI) and Physical Risk Index (PRI) (Bua et al., 2024). While these indices are proxies for perceived rather than objective risk, their broad acceptance in recent literature (see, for example, Bua et al., 2024, Tilly and Livan, 2022) supports their effectiveness at capturing market sentiment. The model allows us to capture time-varying responses and amplification effects across euro-denominated green and conventional corporate bonds, sovereign bonds, and German breakeven inflation rates (BEIR), the benchmark for euro area inflation expectations. We present regime-dependent Generalised Impulse Response Functions (GIRFs) (Ehrmann et al., 2003), which illustrate co-movement dynamics under shocks across regimes. By integrating bond class heterogeneity with regime shifts, this study provides the first empirical assessment of how climate-related risks shape both short- and long-term inflation expectations and bond market dynamics in Europe, contributing to ongoing policy debates about potential de-anchoring from the European Central Bank's (ECB) inflation target.

We address three research questions, namely, (i) How do inflation expectations and bond markets respond to shocks in news-based climate-related risk indices across different volatility regimes? (ii) How do bond returns react to short- and long-term inflation expectation shocks across regimes? (iii) Do shocks to different bond classes result in contagion or decoupling dynamics depending on volatility regimes?

Our findings suggest that bond markets are more sensitive to physical than transition risks, particularly during high volatility regimes. Moreover, only short-term inflation expectations respond significantly to climate-related shocks, while long-term expectations remain broadly anchored. Finally, contagion effects across bond classes are amplified during periods of stress, indicating that volatility intensifies financial linkages and market reactions to climate-related risks. These findings are especially relevant for European institutional investors managing inflation-hedging strategies and green finance mandates, as well as for central banks considering how to integrate climate-related risks into inflation models and financial stability toolkits, since climate-related risks are becoming increasingly structural drivers of macro-financial dynamics shaped not only by fundamentals but also by market sentiment and behavioural responses to volatility.

The remainder of this paper is structured as follows. Section 2 reviews the relevant literature on climate-related risk, inflation expectations, and bond markets. Section 3 outlines the data and econometric methodology while Section 4 presents the empirical findings. Section 5 concludes with a discussion of the results and derives implications for financial stability and monetary policy trade-offs.

## 2 Literature review

This work contributes to various strands of literature, specifically the effects of green transition and physical climate risks on inflation expectations and on bond markets, as well as bond market interactions under different volatility regimes.

While, to the best of our knowledge, inflation expectations have not yet been directly linked to news-based climate-related risks Tilly and Livan (2022) show that daily macro-financial news sentiment drives BEIR across eight countries. Parallel research using survey-based evidence shows that both households and firms adjust their inflation expectations in response to climate concerns, though the direction and persistence of these effects vary across studies (Angelico, 2024; Hensel et al., 2024; Meinerding et al., 2023). Empirical evidence suggests that both physical climate risks and green transition risks can exert inflationary pressures through both supply-side disruptions and transition-related adjustments. Physical risks raise prices by disrupting production, damaging infrastructure, and reducing key inputs, with the magnitude depending on shock intensity, consumption shifts, and fiscal support (Beirne et al., 2021;

Cantelmo, 2022; Cevik and Jalles, 2024; Kabundi et al., 2022; Qi et al., 2025). In contrast, transition risks affect inflation dynamics primarily via firms with high carbon intensity, which face stranded asset risks,[2] rising refinancing costs, and tighter regulation, while lenders face reputational and compliance risks (Chava, 2014; Delis et al., 2024; Generation Foundation, 2013). Beyond firm-level impacts, adaptation costs and supply-side adjustments can transmit these pressures more broadly across sectors, with the macroeconomic outcome shaped by an economy's structure and regulatory environment (Berthold et al., 2024; Cahen-Fourot et al., 2021; Konradt and di Mauro, 2023; Moessner, 2022; Santabárbara and Suárez-Varela, 2022). These phenomena are increasingly referred to as *Greenflation* and *Climateflation* (Schnabel, 2022a,b).

Building on this literature, our study contributes by providing a direct analysis of news-based climate-related risks on BEIR, which serves as a widely used market-based measure of inflation expectations (see e.g. Christensen et al., 2010; d'Amico et al., 2018; Gürkaynak et al., 2010; Strohsal and Winkelmann, 2015). Furthermore, we contribute to the literature of the effects of inflation expectations on bond markets. Rising inflation expectations typically lower real interest rates and bond prices, consistent with Fisher's theory (Fisher, 1930); however, in practice their effects depend on the inflation driver, the business cycle, and expected monetary policy (Chun, 2011). In this vein, Pesci et al. (2022) find that inflation expectations have time-varying effects on corporate bonds, with weaker impacts on investment-grade and stronger sensitivity in high-yield bonds. When inflation is supply-driven, sovereign and corporate bonds tend to face higher risk premia due to worsening economic conditions and fears of prolonged monetary tightening. By contrast, when inflation is demand-driven, sovereign bonds remain more stable and corporate spreads narrower (Bonelli et al., 2025; Cieslak and Pflueger, 2023). Boeckx et al. (2025) relate this to time horizons in that short-term expectations are more influenced by supply shocks whereas long-term expectations are driven more by demand-side factors.

[2] Stranded assets are assets that experience unexpected or early reductions in value, write-offs, or are converted into financial liabilities.

The literature analysing climate-related risks on bond dynamics indicates varying effects across bond classes, raising financial stability concerns. For conventional and green corporate bonds, an important concept is the 'greenium', or the yield discount investors accept on green assets relative to conventional ones, reflecting their expected benefits from the green transition. Empirical evidence confirms the presence of such premia in several markets (e.g., Bolton and Kacperczyk, 2023; Pástor et al., 2022).[3]

While the market for green bonds has grown significantly in recent years, the performance characteristics and drivers of these investments are still relatively under researched. Recent work by Baltas and Mann (2024) shows that green bond indices do not consistently outperform the broader market once financial and commodity factors are accounted for, suggesting limited performance differentiation versus conventional assets. Fernandes and Papadimitriou (2025) find that drought risk increases firm cash holdings in the euro area, especially for unlisted firms, supporting a precautionary motive. Understanding how specific environmental risks translate into corporate financial behaviour is crucial for assessing the broader economic impacts of climate change. The increasing risk of climate-related disasters has also raised awareness of the necessity for regulatory action, prompting policymakers to strengthen environmental regulations (Emam et al., 2020) and investors to anticipate stricter policies, thereby accelerating their transition toward green investments (Choi et al., 2020). Conlon et al. (2024) show that borrower exposure to extreme weather raises lender systemic risk in syndicated loans, and Goodarzi and Meinerding (2025) highlight the value of regime shifts in dynamic allocation during high uncertainty.

Government bonds are similarly affected by climate-related risks, albeit through different channels, as exposure to climate hazards can weaken state finances, raise government risk profiles and borrowing costs, and depress bond prices (Beirne et al., 2021; Cevik and Jalles, 2022; Klusak et al., 2023). Closely related to our work, a growing strand of literature employs the TRI and PRI to analyse bond market dynamics. These studies generally find that climate-related risk effects are time-varying and regime- or quantile-dependent, with the PRI exerting stronger and more consistent impacts on bond pricing than the TRI. Results also

[3] For related evidence, see also Agliardi and Agliardi (2021); Antoniuk and Leirvik (2021); Seltzer et al. (2022).

suggest heterogeneous resilience across bond classes: ESG corporate bonds tend to be more resilient to transition risks, while ESG sovereign bonds are more sensitive to physical risks, and global green bonds exhibit reduced volatility under the PRI but heightened instability when transition risks are unexpectedly low (Bats et al., 2024; Bouri et al., 2023; Cepni et al., 2023, 2022).

This research therefore aligns with work that explores the transmission of shocks in different market volatility regimes. Financial markets are known to exhibit volatility clustering (Cont, 2010), often amplified by behavioural factors such as herding (Schmitt and Westerhoff, 2017; Shiller, 1995), leverage effects (Brunnermeier and Pedersen, 2009; Thurner et al., 2012), and heightened risk aversion leading to safe-haven flows (Kindleberger and Aliber, 1978; Tversky and Kahneman, 1992). Based on Salience Theory (Bordalo et al., 2012), investors in stressed market environments also tend to overweight salient information, systematically under-weighting other risks.

Against this backdrop, several recent studies employ MS-VAR models to analyse regime-specific contagion dynamics in bond markets. Evidence generally shows that contagion across green, sovereign, and corporate bonds becomes stronger under high volatility regimes, with interdependence dominating in calmer periods (Flavin and Sheenan, 2023; Reumkens and Sheenan, 2024; Sheenan et al., 2024). These findings underscore the usefulness of a regime-switching MS-VAR framework for capturing bond market interlinkages under stress, an approach our study extends by explicitly incorporating climate-related risks and inflation expectations.

# 3 Data and Econometric Method

This study explicitly focuses on European financial markets due to the region's regulatory leadership in climate policies and the availability of high-quality, standardised financial and climate-related risk data. The European Union's (EU's) stringent climate regulations and ambitious decarbonisation targets create a unique setting for evaluating the financial implications of climate-related risks (EC, 2019), making it an ideal case for this analysis.

However, we recognise that this framework is subject to political friction, exemplified by the recent ”Omnibus Simplification Package” (EC, 2025; European Climate Neutrality Observatory, 2025), which has attracted criticism for potentially undermining the effective scope of key corporate sustainability directives.[4]

The choice of a daily data frequency is a deliberate methodological decision, dictated by both the nature of our research question and the construction of our key explanatory variables. Our analysis aims to capture the high-frequency dynamics of financial market reactions to news-based climate risk sentiment. Lower frequencies, such as weekly or monthly, would mask these immediate impacts, as the market's response to information shocks is often short-lived. Conversely, an analysis at a higher, intraday frequency is precluded by the availability of the news-based TRI and PRI, which are constructed at a daily aggregation level. Therefore, daily frequency represents the most appropriate temporal resolution to investigate the research question at hand.

Our daily dataset, sourced from Refinitiv/LSEG Datastream, spans October 20th, 2014, to June 24th, 2024. It incorporates climate-related risk data alongside the log returns of five key financial indices: corporate bonds (S&P Euro Corporate Bond Index), green bonds (Bloomberg MSCI Euro Green Bond Index), government bonds (Bloomberg Euro Agg Treasury 10+ Year TR Index), and Breakeven Inflation Rates for Germany (two-year and ten-year maturities).

A key input are the news-based Transition Risk Index and Physical Risk Index developed by Bua et al. (2024), which serve as proxies for market perceptions of transition and physical climate risks. While these indices reflect perceived rather than objective risk exposure, their construction from aggregated news sentiment makes them well-suited to capture evolving market narratives. We acknowledge their limitations, including potential biases from the underlying news sources and the inherent challenges of Natural Language Processing.

[4]The European Commission's Omnibus Simplification Package (February 2025) is a legislative initiative ostensibly designed to reduce administrative burden on firms. It has been widely criticized as a regulatory rollback (Merler, 2025), particularly for amendments to the Corporate Sustainability Reporting Directive and the Corporate Sustainability Due Diligence Directive. Supervisory authorities, including the ECB, have warned that drastically raising reporting thresholds and eliminating data points will diminish the availability and reliability of standardized sustainability data, potentially leading to 'systematic and unquantifiable bias' in financial risk management (ECB, 2025).

Nevertheless, their growing acceptance in the literature (e.g., Bua et al., 2024, Tilly and Livan, 2022) underscores their value as indicators of climate-related risk sentiment.

Our analysis relies on bond indices rather than individual securities. While this approach effectively captures broad market-level dynamics, it abstracts from issuer-level effects and does not explicitly control for idiosyncratic bond characteristics. This design choice allows us to focus on macro-level interactions across major bond segments and inflation expectations. For BEIRs, we follow Pesci et al. (2022) and use German inflation-linked bonds as a reliable proxy for broader European implied inflation expectations due to their superior liquidity. To capture both short- and long-term dynamics, we include the two-year BEIR and the ten-year BEIR, with the latter being a standard measure for long-term inflation compensation (Church, 2019).

We furthermore acknowledge that our dataset relies on bond indices rather than individual securities. While this approach effectively captures broad market-level dynamics, it inherently abstracts from issuer-level effects and purposefully does not explicitly control for idiosyncratic bond characteristics (liquidity or maturities). This design choice allows us to focus on macro-level interactions across major bond segments and inflation expectations.

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All series are transformed to ensure stationarity. Financial indices are in log returns, while BEIR series are first-differenced.[5] Augmented Dickey-Fuller (ADF) tests confirm that all

[5]Formally, we compute the log-difference of BEIRs, $r_t = \log(\pi_{t+1}) - \log(\pi_t)$, to maintain parsimony.

series are stationary at conventional significance levels, ensuring their suitability for econometric modelling.[6] Descriptive statistics and time series plots are presented in Appendix A.

Finally, given the context-dependency of our empirical approach, our findings should be interpreted primarily within the European context and are not necessarily transferable to other regions with different economic structures, risk profiles, or policy frameworks.

The applied MS-VAR model effectively captures the non-linear, time-varying dynamics typical of financial markets (Cont, 2010), enabling us to assess how climate-related risks and inflation expectations influence bond markets under different volatility regimes, an essential factor for risk management and portfolio allocation. Similar methods have also been applied to optimal portfolio strategy analysis, as shown in Goodarzi and Meinerding (2025).

The model is given by:

$$y_{i,t} = \alpha(s_t) + \sum_{k=1}^{K} \beta_k(s_t) y_{i,t-k} + \epsilon_{i,t}^{st}, \tag{1}$$

$$s_t \in \{1, 2\},$$

$$\epsilon_{i,t}^{st} \sim i.i.d.N(0, \sigma_s^2),$$

where $y_{i,t}$ is an n-dimensional time series vector of dependent variables, given by the above presented time series.$\alpha$ is a matrix of state-dependent intercepts, $\beta_1$ .. $\beta_k$ are matrices of the state-dependent auto-regressive coefficients and capture the relationships between our variables, and $\epsilon_{i,t}^{st}$ is a state-dependent noise vector, which has a zero mean and constant variance within each regime. $s_t$ is an unobserved random variable that signals the switch from one regime to another. K is the lag length, following the suggestions of the Hannan–Quinn Information Criterion and is set to 1. Since the true regime cannot be observed, we must specify the paths by which the regimes transit from one to another. We assume $s_t$ follows a first-order Markov process in which the current regime, $s_t$ relies only on the regime one period in the past, $s_{t-1}$.

We estimate the model using a Bayesian Markov Chain Monte Carlo approach with specified prior distributions: a Wishart distribution for variances, a flat prior for VAR coefficients, and a

[6] All results available upon request.

weak Dirichlet prior for transition probabilities favoring state persistence. Employing Gibbs sampling, we estimate parameters and regimes by sequentially drawing sigmas given mean coefficients and regimes, then drawing mean coefficients ($\alpha$ and $\beta$) given sigmas and regimes, followed by drawing regimes given sigmas and mean coefficients, and finally drawing the transition parameters. This sequence is repeated 10,000 times after discarding an initial burn-in of 2,000 iterations. With the estimated parameters, we generate regime-dependent GIRFs and their associated confidence bands.

The model identifies two volatility regimes: low (Regime 1) and high (Regime 2), with high volatility periods occurring in distinct clusters. While the regime classification is based on European data, several international events triggered significant spillovers into European markets. Figure 1 presents the smoothed probabilities of the high volatility regime.

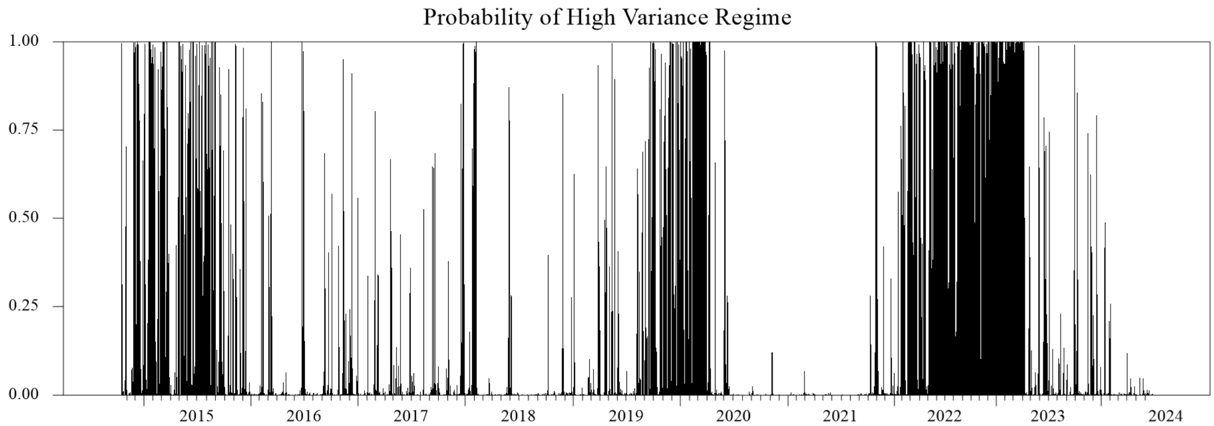


Figure 1: Smoothed probabilities of the high volatility regime (TRI and two-year BEIR).

Notes: Estimated using the MS-VAR model, this figure highlights periods of increased financial market stress and their alignment with major economic and geopolitical events.

It is clear from Figure 2 that while the system predominantly remains in the low volatility regime, three distinct periods of significant volatility clustering are identified. The first volatility cluster emerges in 2015, with key events intensifying market fluctuations as the European Securities and Markets Agency (ESMA) reports. In January 2015, the Swiss Franc Shock caused a sudden appreciation of the franc, leading to losses for European exporters. By mid-2015, the Greek Debt Crisis triggered sovereign bond turbulence, particularly in Greece and peripheral EU nations (ESMA, 2015). The Chinese Stock Market Crash (June–August 2015) resulted in a global selloff, culminating in Black Monday (August 24, 2015).

Furthermore, the U.S. Federal Reserve rate hike (December 2015) increased capital outflows from emerging markets, adding to bond market instability (ESMA, 2016). Meanwhile, the Paris Agreement was adopted in December 2015, with the EU showing great support for it (EC, 2016).

A second, intense volatility period spans mid-2019 to mid-2020. In mid-2019, European sovereign bond yields hit historic lows, driven by ECB interest rate cuts and economic uncertainty (ESMA, 2019). In December 2019, the European Commission (EC) announced the European Green Deal, also giving an outlook on the Green Financing Strategy and highlighting the role of the public sector in it (EC, 2019). Following on this, (ESMA, 2020a) acknowledges the growing importance of ESG considerations among investors. In March–April 2020, the COVID-19 market turmoil caused market stress (ESMA, 2020b).

The most persistent volatility phase occurs between 2022 and mid-2023, corresponding to overlapping crises. The Russian invasion of Ukraine in February 2022 led to significant turmoil in energy markets (ESMA, 2022). The subsequent European energy crisis, spanning from June to September 2022, saw gas prices peak in August due to supply shortages, prompting government interventions, as discussed in the same report. Following the announcement of the Fit for 55 initiative (EC, 2023), increased volatility in carbon pricing and green investments were observed (ESMA, 2023a). Throughout 2023, particularly in January and July–August, ongoing energy market instability continued to impact electricity, natural gas, and carbon credit markets (ESMA, 2023b).

The summary statistics presented in Table 1 provide a detailed characterization of these two distinct regimes identified in the MS-VAR model. The findings reveal differences in terms of persistence, volatility, and inflation expectation dynamics, depending on whether the model includes the TRI or the PRI in conjunction with the two-year or ten-year BEIRs.

We identify regimes according to volatility, with Regime 2 characterised by substantial increases in standard deviations of all variables, particularly in BEIRs. When the two-year BEIR is included in the model, its variance increases almost 50-fold. In contrast, the ten-year BEIR exhibits a more moderate rise in standard deviation, suggesting that shorter-term

Table 1: Regime-Specific Summary Statistics for Transition Risk (Panel A) and Physical Risk (Panel B)

**Panel A: Transition Risk**

| **Parameters** | **2-Year BEIR** | | **10-Year BEIR** | |
|---|---|---|---|---|
| | **Regime 1** | **Regime 2** | **Regime 1** | **Regime 2** |
| Probability to stay in regime | 0.92 | 0.78 | 0.93 | 0.80 |
| Regime Frequency (%) | 73.41 | 26.59 | 71.86 | 28.14 |
| Avg. Crisis Duration (Periods) | – | 4.81 | – | 5.00 |
| **Standard Deviation** | | | | |
| Transition Risk | 0.0197 | 0.0253 | 0.0197 | 0.0255 |
| Corporate Bond | 0.0000 | 0.0032 | 0.0000 | 0.0032 |
| Sovereign Bond | 0.0045 | 0.0100 | 0.0045 | 0.0105 |
| Green Bond | 0.0000 | 0.0032 | 0.0000 | 0.0032 |
| Two-year BEIR | 0.0448 | 0.3062 | – | – |
| Ten-year BEIR | – | – | 0.0221 | 0.0418 |

**Panel B: Physical Risk**

| **Parameters** | **2-Year BEIR** | | **10-Year BEIR** | |
|---|---|---|---|---|
| | **Regime 1** | **Regime 2** | **Regime 1** | **Regime 2** |
| Probability to stay in regime | 0.93 | 0.78 | 0.93 | 0.80 |
| Regime Frequency (%) | 74.05 | 25.95 | 73.03 | 26.97 |
| Avg. Crisis Duration (Periods) | – | 4.39 | – | 5.58 |
| **Standard Deviation** | | | | |
| Physical Risk | 0.0197 | 0.0228 | 0.0200 | 0.0219 |
| Corporate Bond | 0.0000 | 0.0032 | 0.0000 | 0.0032 |
| Sovereign Bond | 0.0045 | 0.0100 | 0.0045 | 0.0105 |
| Green Bond | 0.0000 | 0.0032 | 0.0000 | 0.0032 |
| Two-year BEIR | 0.0452 | 0.3077 | – | – |
| Ten-year BEIR | – | – | 0.0226 | 0.0421 |

Notes: This table summarises regime-specific characteristics from the MS-VAR model. Regime 1 is the low volatility state; Regime 2 is the high volatility (crisis) state. The probability of remaining in each regime is derived from the transition probability matrix. The average duration of each state is computed as $1/(1 - P(i,i))$. Standard deviations are the square roots of the diagonal elements of the residual covariance matrix ($\Sigma$).

*Column mapping:* Columns 2–3 report statistics for specifications that include the **two-year** BEIR; columns 4–5 refer to specifications that include the **ten-year** BEIR. Accordingly, the BEIR rows report regime-specific standard deviations only for the maturity included in the corresponding specification.

inflation expectations respond more aggressively to regime shifts. This disparity likely reflects differences in how inflation expectations are formed across horizons. Short-term expectations, as captured by the two-year BEIR, are more reactive to immediate shocks, such as supply chain disruptions, geopolitical events, or abrupt monetary policy adjustments (Boeckx et al., 2025). In contrast, long-term expectations, reflected in the ten-year BEIR, tend to be more anchored, as they incorporate central bank credibility and structural inflation trends (Boeckx et al., 2025; Diegel and Nautz, 2021; Yetman, 2020). Additionally, investors may adjust their short-term inflation outlook more frequently in response to market volatility, whereas long-term expectations remain relatively stable unless a fundamental shift in monetary policy or economic conditions occurs (Boeckx et al., 2025; Diegel and Nautz, 2021; Pesci et al., 2022).

The standard deviation of transition risk and physical risk remains relatively stable across both regimes, indicating that while these risks contribute to the transition between states, their own volatility does not change substantially. However, bond market dynamics exhibit moderate shifts: the variance of sovereign bonds and green bonds increases by a factor of 5–10% in Regime 2, while corporate bonds show minimal variance changes, suggesting that sovereign debt instruments and green assets are more sensitive to shifts in market volatility. Across all specifications, Regime 1 (low volatility state) exhibits a high degree of persistence with an average duration of around five days. Conversely, Regime 2 (high volatility state) is less persistent with a shorter duration.

# 4 Results and Discussion

To assess the impact of climate-related risks on inflation expectations and bond markets, we present the model's estimated results using GIRFs. These allow us to examine the shock transmission dynamics among the variables, revealing how a shock to one asset class or risk factor can impact others across different volatility regimes. Understanding these potential interdependencies and contagion effects (Dungey et al., 2020) is crucial for financial market participants in managing portfolio risk and assessing systemic vulnerabilities[7]. To improve interpretability and provide context, for each shock a short example relating to our data will be initially introduced.[8]

It is crucial to clarify that our use of GIRFs within the Bayesian MS-VAR framework provides a statistical characterisation of regime-dependent shock transmission and co-movement dynamics, rather than a structural identification of causal contagion channels. Shocks are treated as reduced-form innovations $\varepsilon_t \,|\, S_t = s$ drawn from the regime-specific covariance matrix $\Sigma_s$. No contemporaneous or sign restrictions are imposed, so the responses are invariant to variable ordering but remain model- and distribution-dependent, and should therefore not be interpreted as causal. This reduced-form perspective is well-suited to our objective of examining how TRI and PRI interact with bond market variables across volatility regimes. While structural identification schemes, such as recursive orderings or sign restrictions, are possible, they require strong and potentially contested priors and thus lie beyond the scope of this paper. From a risk-management standpoint, structural identification is not essential as GIRFs quantify the size, direction, and persistence of generalised shocks, offering robust insights into spillovers and connectedness without committing to a specific structural scheme. Accordingly, we emphasise predictive interdependence rather than causation. Significant lagged cross-effects indicate that variables help forecast one another conditional on regime, though formal Granger causality requires explicit, regime-specific testing. All GIRFs are conditional on the initial regime and the transition matrix, and we report the shock scaling (one standard deviation) and conditioning choices to make this dependence transparent.

We further examine how shocks transmit to inflation expectations and bond markets across regimes by analysing cross-regime changes in the comovement of variables. Following Dungey et al. (2020), we classify these dynamics into three categories: contagion, where comovement among the shocked and other variables increases in the high volatility regime;

[7]The results are visualised in a multi-panel figure, where rows represent different asset classes and columns indicate the respective volatility regimes, allowing for a structured comparison of shock transmission patterns of a representative one-standard-deviation shock. Each panel displays the GIRF for the specified asset and regime, along with its 95% confidence intervals. The black lines represent the estimated effects, while the blue lines denote the confidence intervals. The scale remains consistent across regimes (columns) but varies between asset classes (rows).

[8]Note: Given the model's symmetry, these shocks can be viewed as either positive or negative.

interdependence, where comovement remains unchanged across regimes; and decoupling, where comovement decreases under high volatility. This classification captures whether climate-related and other shocks statistically intensify financial linkages (contagion), preserve their stability (interdependence), or weaken connections (decoupling). In our setting, comovement refers to both the strength and persistence of response activity relative to the shocked variable observed in the regime-dependent impulse responses.

This framework provides a rigorous description of observed co-movement patterns and helps to identify whether shifts in volatility regimes reflect structural market changes or heightened investor sensitivity to specific shocks. The dynamics across specifications generally display a high degree of similarity and are therefore described jointly, with explicit discussion of any deviations. Such deviations may signal evolving structural conditions or non-linear amplification effects during financial stress. Importantly, we emphasise that these are statistically observed co-movement dynamics rather than deeper structural contagion mechanisms, which we highlight as avenues for future research.[9]

## 4.1 Shock Transmission of Transition Risk to Inflation Expectations and Bond Markets

An example of a green regulatory shock occurred in July 2021 with the announcement of a more restrictive policy on carbon emission allowance supply within the EU Emissions Trading System under the Fit for 55 initiative, intending to raise carbon prices (EC, 2021). Figures 2 and 3 illustrate the regime-dependent response to a shock in the TRI.

[9] Our approach identifies regime-dependent co-movement patterns without imposing structural causal assumptions, which would require strong priors on variable ordering and shock identification.

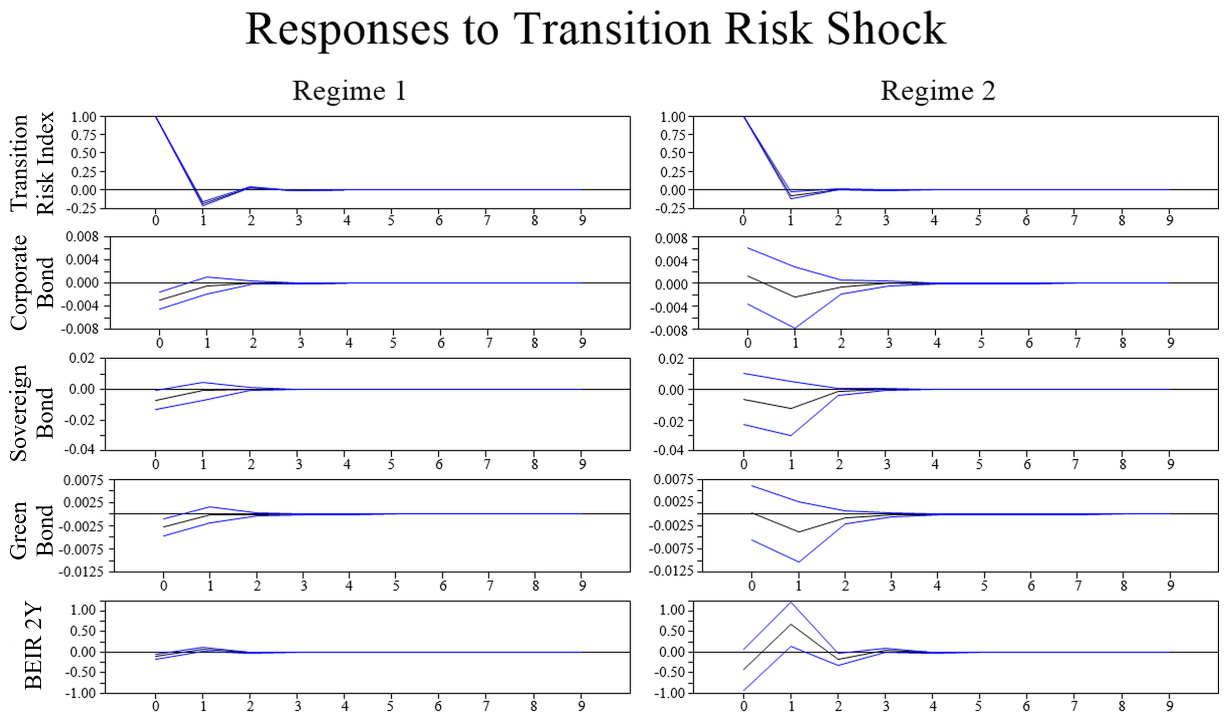


Figure 2: GIRFs illustrating the effects of an exogenous shock to the TRI on two-year BEIR, as well as various bond classes, under low- and high volatility regimes. Solid black lines indicate the estimated responses, while blue bands represent 95% confidence intervals.

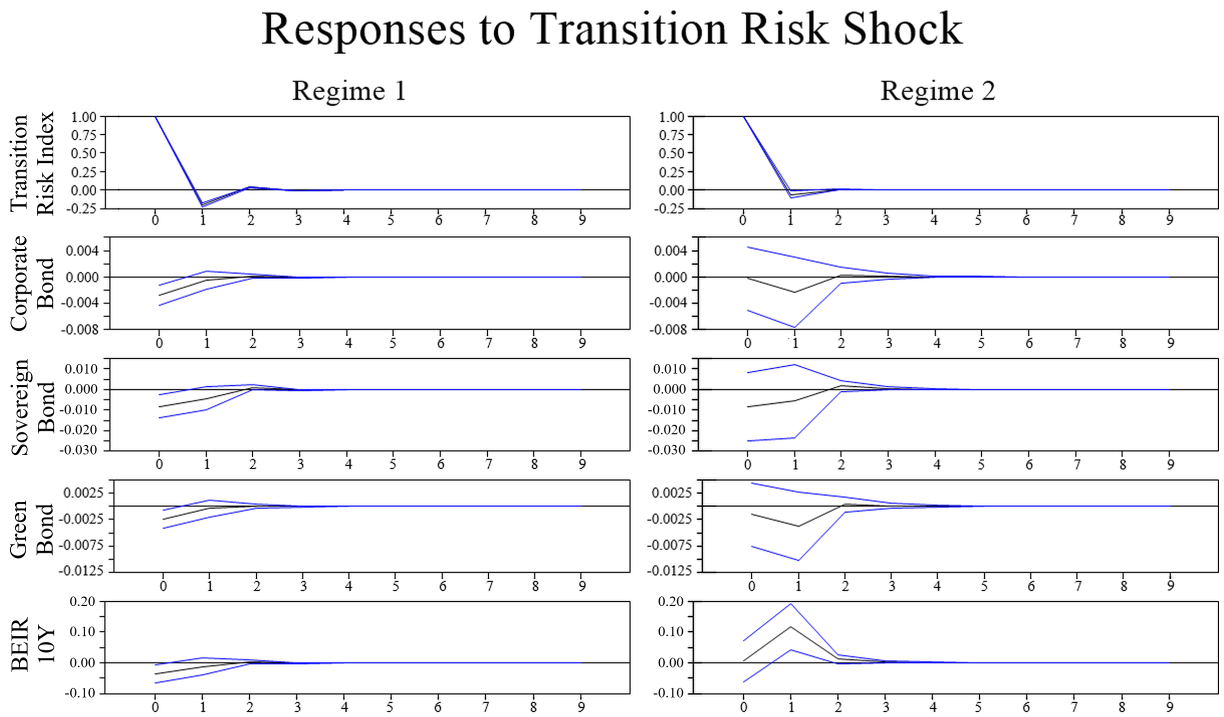


Figure 3: GIRFs illustrating the effects of an exogenous shock to the TRI on ten-year BEIR, as well as various bond classes, under low- and high volatility regimes. Solid black lines indicate the estimated responses, while blue bands represent 95% confidence intervals.

In both Figure 2 and Figure 3, in the low volatility regime (Regime 1), the TRI exhibits a negative rebound at period one before converging. Green bonds, corporate bonds, and sovereign bonds display nuanced but significant negative reactions. Additionally, the two-year and ten-year BEIR show slight negative responses. In the high volatility regime (Regime 2), the TRI response remains unchanged. However, green bonds, corporate bonds, and sovereign bonds no longer exhibit a significant reaction, indicating decoupling. In contrast, both BEIRs, display a significant positive effect with widened confidence interval (CI) bands, with the two-year maturity reacting more strongly than the ten-year maturity, indicating contagion.

Our robustness checks in Figure C.8 and Figure C.9 yield similar patterns. While the nuanced effects on bonds dissipate in the low volatility regime, the confidence intervals of the BEIRs widen further and encompass the zero line. Accordingly, regarding inflation expectations, we find that increased news coverage of the green transition leads to a slight but robust decline in two-year but not ten-year inflation expectations in the low volatility regime. This aligns with the intuition that inflationary effects are more pronounced in the short-term. Yet long-term inflation expectations remain more anchored, as markets anticipate that the ECB will guide inflation toward its target (Bernanke, 2007; Christelis et al., 2020).

Our findings indicate that the bond classes analysed are at most negatively affected in the low volatility regime, while they show no significant effects in the high volatility regime. This suggests that in periods of heightened volatility, investors' attention may be more focused on immediate or prominent risks, reducing the influence of transition concerns. This aligns with theoretical expectations that in turbulent markets, less salient risks receive less weight in decision-making (Bordalo et al., 2012). The given high volatility periods align with key crises, such as the aftermath of the euro crisis, the COVID-19 pandemic, and geopolitical instability, including the Russian conflict, during which investors prioritised pressing financial and economic concerns over transition risks. In addition, the divergence between green and corporate bonds remains relatively subtle. This is in line with the assessment of European authorities that the taken policy measures facilitate a gradual, structured transition and should not cause sudden disruptions (ECB, 2022).

## 4.2 Shock Transmission of Physical Climate Risk to Inflation Expectations and Bond Markets

One example of a physical climate shock would be the summer 2022 heatwave, which triggered one of Europe's most severe droughts in recent history, leading to critically low water levels in major rivers. This event had far-reaching consequences across agriculture, energy production, and transportation (Toreti et al., 2022). Figures 4 and 5 illustrate distinct regime-dependent dynamics following a shock to PRI.

In the low volatility regime (Regime 1), the PRI exhibits a negative rebound at period one before converging. Corporate bonds and green bonds exhibit nuanced but significantly negative reactions while sovereign bonds remain insignificant. The ten-year BEIR reacts negatively whereas the two-year BEIR exhibits no significant response. In the high volatility regime (Regime 2), the PRI follows a similar pattern, converging at period two after a small negative rebound at period one. All bond classes exhibit marginal reactions in both specifications, though with slight variations.

In Figure 4, green and corporate bonds exhibit a slightly stronger negative response. Sovereign bonds initially show no significant reaction but all experience a marginal negative effect at period two, indicating contagion. In Figure 5, green and corporate bonds react like before, suggesting interdependence. Sovereign bonds show a slight negative response when the shock occurs, turning marginally positive at period one, suggesting contagion but with some correction effects. Additionally, the two-year BEIR exhibits a notable significant positive impact when the shock occurs. At the same time, the ten-year BEIR turns significantly positive at period one, indicating contagion for both BEIR horizons.The robustness checks in Figure C.6 and Figure C.7 broadly confirm these results, reinforcing the observed effect patterns for bond classes and the two-year BEIR.

The robustness checks in Figure C.6 and Figure C.7 broadly confirm these results, reinforcing the observed effect patterns for bond classes and the two-year BEIR. In contrast, the findings for the ten-year BEIR are not consistent. This pattern suggests that markets respond faster to physical climate risk news in the short-term while long-term inflation expectations remain more

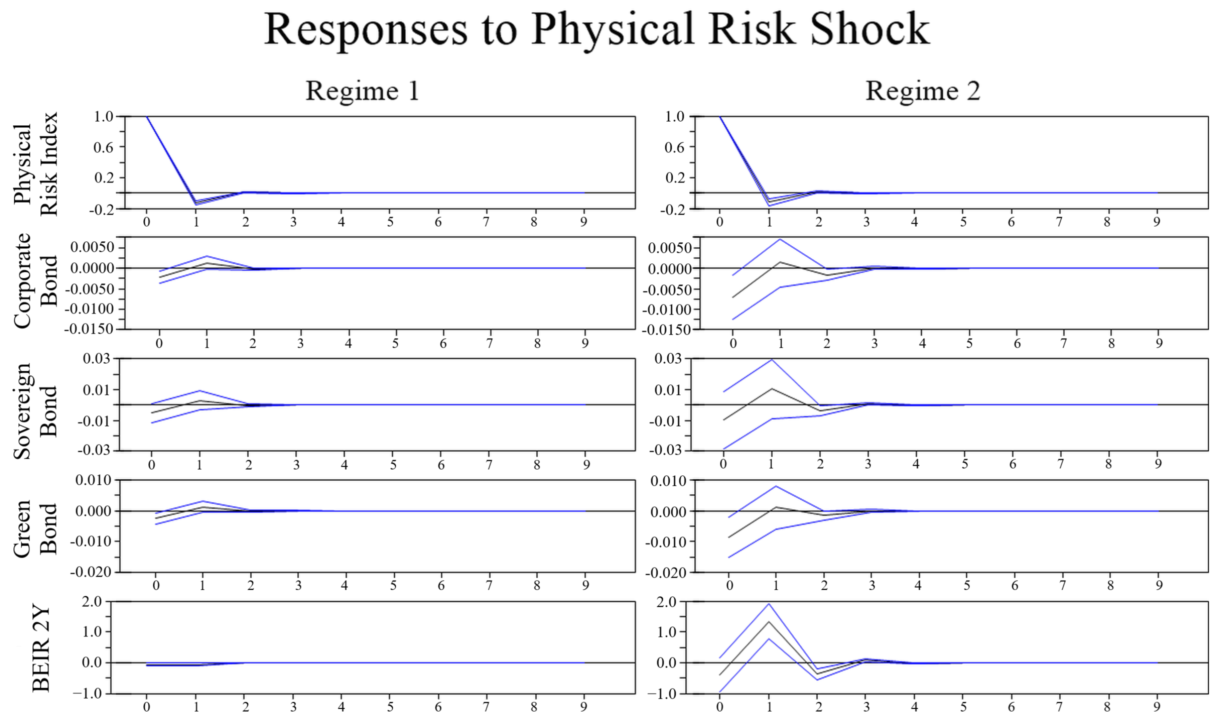


Figure 4: GIRFs displaying the effects of an exogenous shock to the PRI on two-year BEIR and bond markets under different volatility regimes. Solid black lines indicate the estimated responses, while blue bands represent 95% confidence intervals.

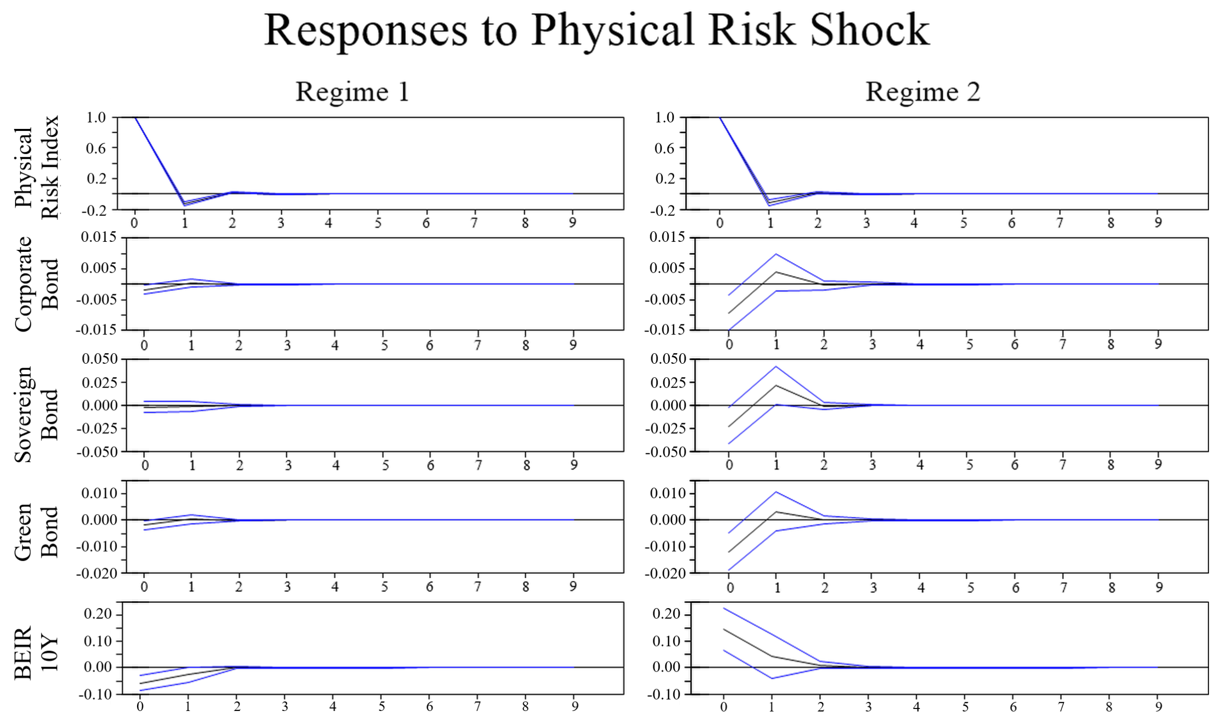


Figure 5: GIRFs displaying the effects of an exogenous shock to the PRI on ten-year BEIR and bond markets under different volatility regimes. Solid black lines indicate the estimated responses, while blue bands represent 95% confidence intervals.

stable. In contrast, the findings for the ten-year BEIR are not consistent. This pattern suggests that markets respond faster to physical climate risk news in the short-term while long-term inflation expectations remain more stable. This is consistent with the expectation that, while rising long-term expectations highlight their structural importance, markets maintain confidence in the ECB's ability to ensure long-term price stability. In terms of bonds, physical climate risk news has a negligible influence on sovereign debt across both regimes, reflecting their safe-haven status and lower sensitivity to non-systemic shocks. Green and corporate bonds are negatively affected in both regimes, but the impact is stronger in the high volatility regime, indicating contagion. This suggests that as firms face greater financial and operational risks, investors anticipate higher costs and weaker economic activity due to physical climate-related damages. Additionally, the increased systematic risk exposure of these asset classes to physical climate events during market downturns, prompting investors to incorporate such risks into portfolio stress testing and scenario analysis, behavioural factors (see Schmitt and Westerhoff (2017) and Thurner et al. (2012)) likely amplify the effects, leading to stronger market reactions in high volatility market regimes.

## 4.3 Shock Transmission of Inflation Expectations to Bond Markets

Boeckx et al. (2025) find that two-year inflation expectations are more sensitive to supply shocks, while ten-year inflation expectations are primarily influenced by demand factors such as economic growth and interest rate expectations. Accordingly, an appropriate example of an upward shock to short-term inflation expectations is the Russian invasion of Ukraine in early 2022. This event triggered severe disruptions in the energy supply, increased energy prices, and increased economic uncertainty, ultimately increasing short-term inflation expectations throughout Europe (Lane, 2022). In the same vein, concerning a shock to ten-year inflation expectations, an example is the roll-out of COVID-19 vaccines in early 2021, which improved the economic outlook amid deflationary pressures and led to higher inflation forecasts (Arnold, 2021).[10]

[10]Moving forward, it is important to note that since all model variables are treated as dependent, the TRI and PRI are not driven by bond markets, though correlations may arise from shared macroeconomic influences or reverse causality.

Figures 6 and 7 illustrate the dynamics following a positive shock to the two-year BEIR ahead. In the low volatility regime (Regime 1), the two-year inflation expectation proxy converges directly at period one. Corporate bonds and sovereign bonds remain unaffected in all periods. Green bonds also do not exhibit a response in Figure 6; however, in Figure 7, they display a marginally significant positive effect in period one. The TRI follows a brief oscillatory pattern. The PRI does not exhibit any significant response. In the high volatility regime (Regime 2), the two-year BEIR experiences a negative rebound at period one before returning to baseline at period two. Corporate bonds, sovereign bonds, and green bonds exhibit oscillatory patterns, showing no significant movement at the time of the shock, followed by a negative reaction at period one and full convergence at period two, indicating a stronger shock transmission, classified as contagion. The TRI's and PRI's relationship to the shocked variable remains unchanged across regimes.

Figures 8 and 9 illustrate the propagation of a positive shock to the ten-year BEIR. In the low volatility regime (Regime 1), the ten-year BEIR converges at period one. Corporate bonds and green bonds remain insignificant at the time of the shock but exhibit a positive reaction. Sovereign bonds show no measurable reaction. The TRI and PRI display no significant response across all periods. In the high volatility regime (Regime 2), the ten-year BEIR undergoes a more prolonged adjustment. Corporate bonds, sovereign bonds, and green bonds exhibit a delayed response and an extended adjustment period, classified as contagion. The TRI and PRI remain insignificant throughout.

Regarding the effect of a shock on short-term inflation expectations the robustness checks in Figure C.10 and C.11 support all findings. There are negligible responses in the low volatility regime but in the high volatility regime there are significant yet nuanced negative effects across bond classes. This suggests that, in high volatility regimes, bond markets price in inflationary risks more sharply, potentially due to concerns over monetary tightening and increased discounting of future bond payments (Cochrane, 2022; Dai et al., 2007; Song, 2017). For portfolio managers, this sensitivity underscores the importance of actively managing interest rate risk and inflation hedging strategies during periods of market stress. Understanding the effects of inflation expectations on bonds requires acknowledging that expected real interest

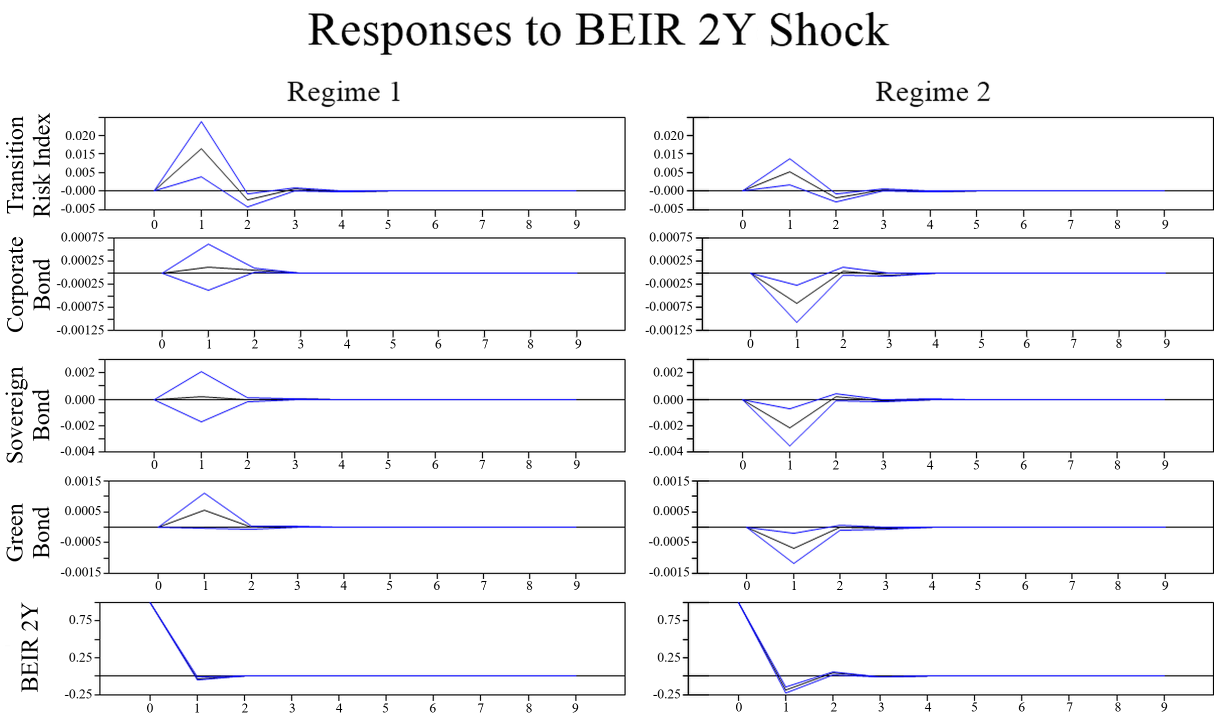


Figure 6: GIRFs illustrating the impact of an exogenous shock to the two-year BEIR on TRI and bond markets across volatility regimes. Solid black lines indicate the estimated responses, while blue bands represent 95% confidence intervals.

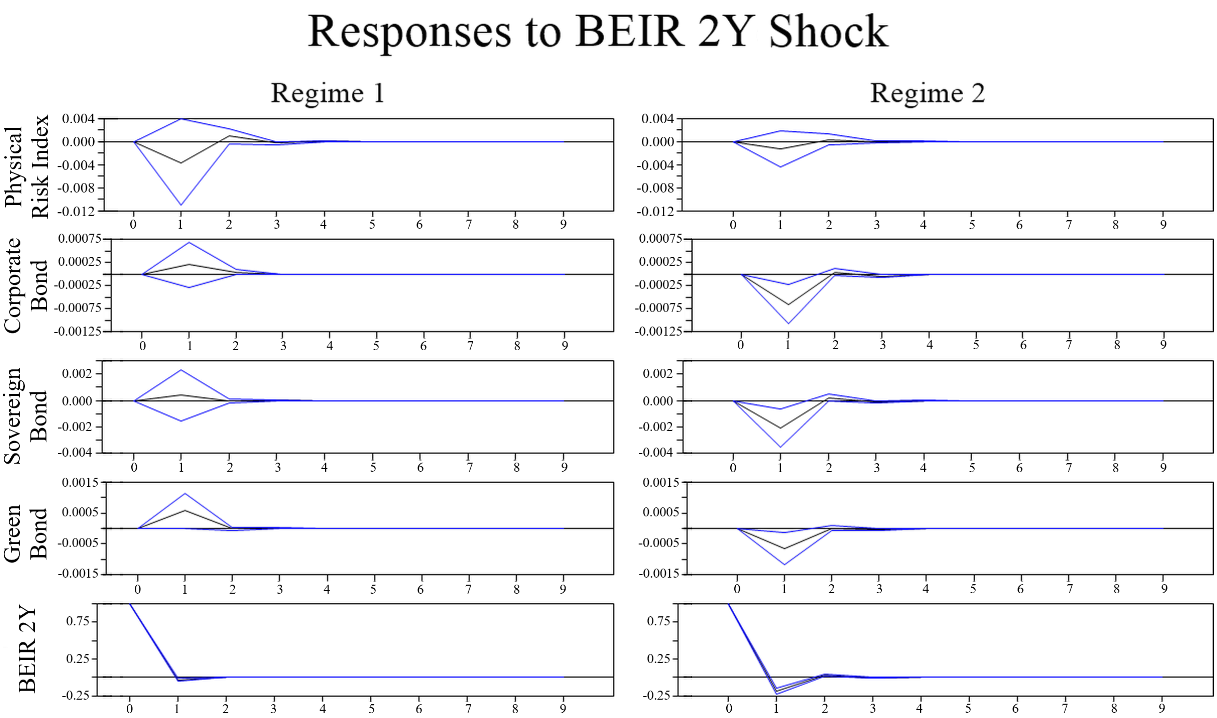


Figure 7: GIRFs illustrating the impact of an exogenous shock to the two-year BEIR on PRI, and bond markets across volatility regimes. Solid black lines indicate the estimated responses, while blue bands represent 95% confidence intervals.

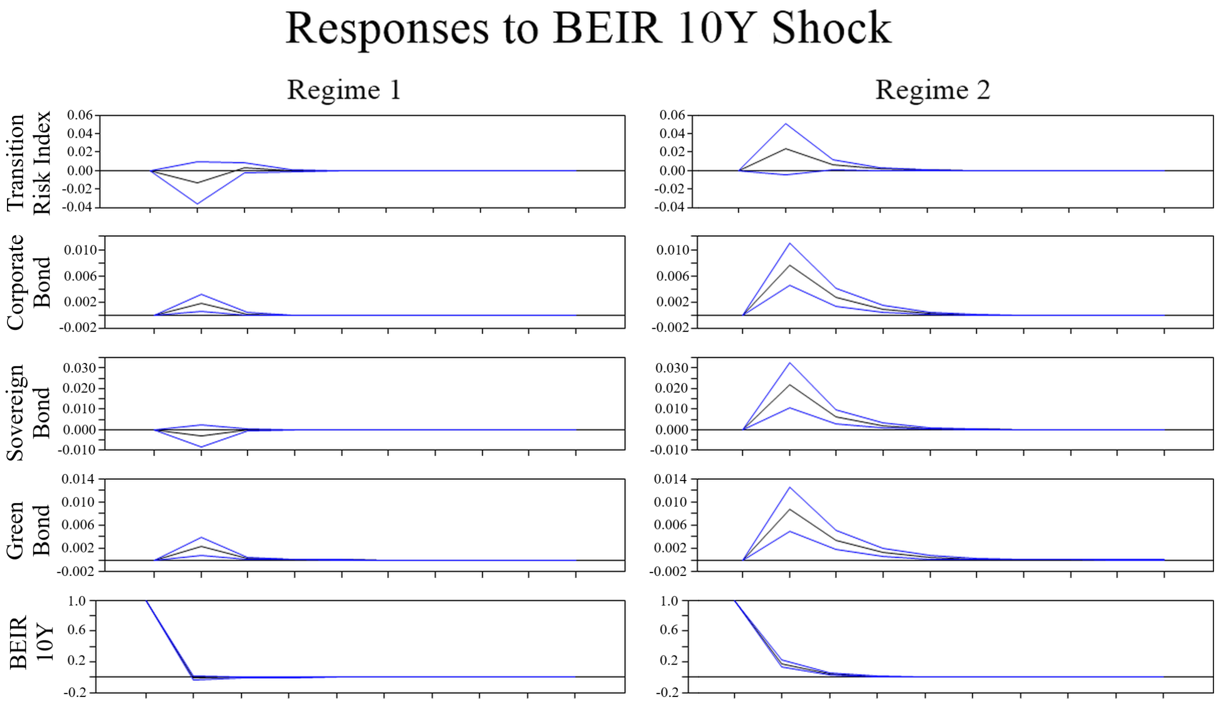


Figure 8: GIRFs showing the transmission dynamics of a ten-year BEIR shock on TRI and bond markets. Solid black lines indicate the estimated responses, while blue bands represent 95% confidence intervals.

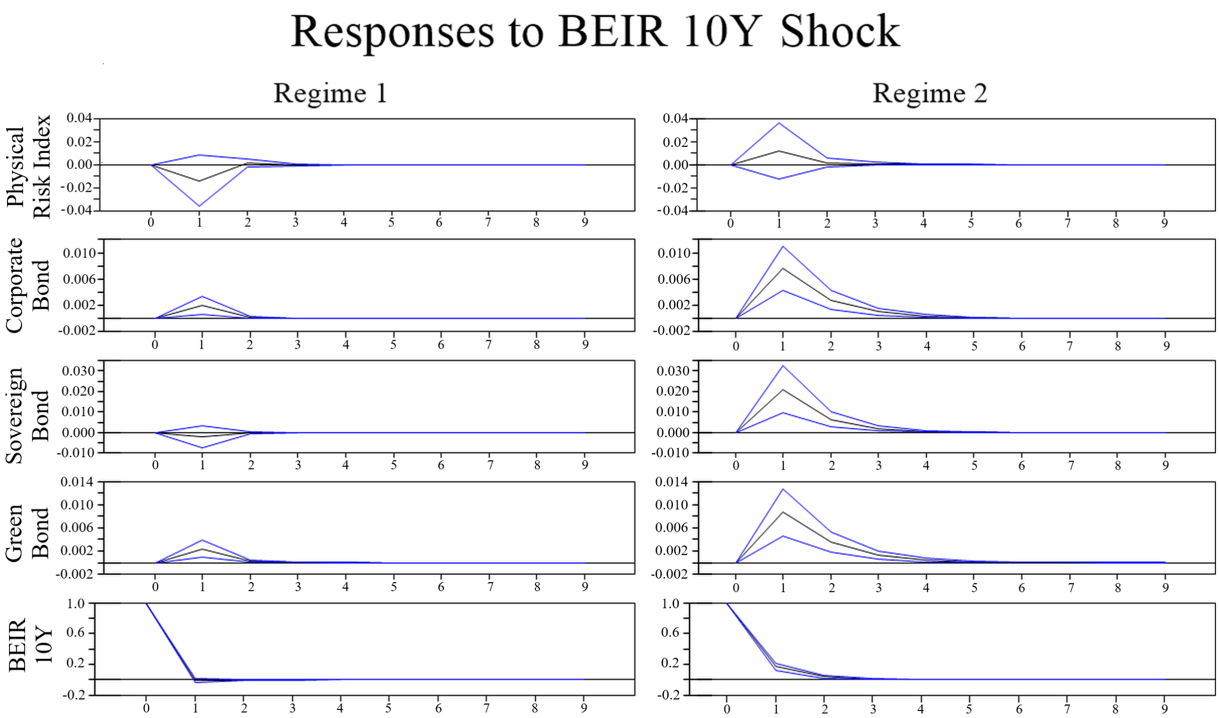


Figure 9: GIRFs showing the transmission dynamics of a ten-year BEIR shock on PRI and bond markets. Solid black lines indicate the estimated responses, while blue bands represent 95% confidence intervals.

rates depend on anticipated monetary policy decisions. In light of the provided example, the ECB initially interpreted the shock as transitory and hesitated to tighten its monetary policy. Moreover, in the other high volatility clusters outlined in Section 2, market circumstances constrained the ECB from adopting a hawkish stance[11]. In this context, the declining real value of bond payments further eroded investor confidence, reinforcing bond market instability.

The findings on the effects of shocks to ten-year horizon inflation expectations are similarly robust (see Figure C.12 and C.13) with the exception of effects on bond classes in the low volatility regime. In contrast, the high volatility regime generates robust positive responses across all bond classes. While higher long-term inflation expectations may coincide with stronger economic prospects in specific contexts, they can also signal heightened inflation risks, prompting concerns about future monetary tightening (Diegel and Nautz, 2021; Jarociński and Karadi, 2020). In this vein, Chen et al. (2023) show that in times of uncertainty and inflation-induced market volatility, investors seek a safe haven in fixed income, having a positive impact on bond returns and partially offsetting the negative effects of inflation on bond prices. Overall, the results of both inflation expectation horizons indicate stronger reactions to their own shocks in high volatility periods, broadly in line with Grishchenko et al. (2017), Corsello et al. (2021), and Istrefi and Piloiu (2014).

## 4.4 Shock Transmissions among Bond Classes

Finally, we examine the mutual effects of shocks across bond classes. To provide context, we introduce examples of such shocks. For corporate bonds, a positive shock can result from fiscal stimulus targeting the broader economy, as seen by the Next Generation EU program, a €750 billion recovery instrument aimed at supporting post-pandemic economic recovery (Havlik et al., 2021). For green bonds, a relevant positive shock stems from fiscal stimulus directed at the green economy, such as the European Green Deal Investment Plan, which aims to mobilise at least €1 trillion over the next decade to accelerate the transition to climate neutrality (European Environment Agency, 2024b). For sovereign bonds, a positive shock can

[11] Following the sovereign debt crisis, exemplified by the cluster around 2015 and the COVID-19 pandemic, inflation remained low, even implying deflationary risks. As a result, the ECB prioritised supporting investment and economic growth (Benigno et al., 2022; Riet, 2017)

arise from flight-to-safety dynamics, as observed during the onset of COVID-19 in early 2020, when investors sought refuge in sovereign debt amid heightened economic uncertainty (ESMA, 2021).

Figures 10, 11, 12 and 13 illustrate the system's response to a positive shock from the corporate bond variable. In the low volatility regime (Regime 1), corporate bonds exhibit a quick convergence. Green bonds respond with equal strength and converge directly. Sovereign bonds also react positively but with more than three times the magnitude of the corporate bond shock. The two-year BEIR and the ten-year BEIR respond negatively at the time of the shock, with shock amplification reaching approximately six times the corporate bond shock. The TRI remains insignificant, while the PRI exhibits brief oscillatory behaviour. In the high volatility regime (Regime 2), corporate bonds exhibit monotonic convergence until period three following the shock. Green bonds and sovereign bonds respond similarly positively, yet with longer convergence, both indicating contagion patterns. The two-year BEIR also exhibits a significant negative reaction at period one, stabilising by period three, while the ten-year BEIR reacts negatively at the time of the shock and converges by period one. The TRI response varies across specifications, for example in Figure 10, it exhibits a slight increase with heightened uncertainty, whereas in Figure 11, it remains insignificant. Similarly, the PRI does not exhibit a significant effect.

Figure 14, 15, 16 and 17 illustrate the response following a shock to the green bond index. In the low volatility regime (Regime 1), green bonds exhibit monotonic convergence at period one. Corporate bonds respond positively at period one. Sovereign bonds show no significant reaction. The two-year BEIR initially rises at the time of the shock, undergoing a negative adjustment at period one. The ten-year BEIR remains unresponsive. Similarly, the TRI shows no reaction, while the PRI responds with short-lived fluctuations. In the high volatility regime (Regime 2), green bonds mirror their behavior in the low volatility regime. Corporate bonds and sovereign bonds exhibit a positive effect at period one, with extended adjustments, indicating stronger shock transmission and, thus, contagion. In contrast, the two-year BEIR remains unchanged across all periods. Finally, the ten-year BEIR, the TRI and the PRI show no meaningful responses.

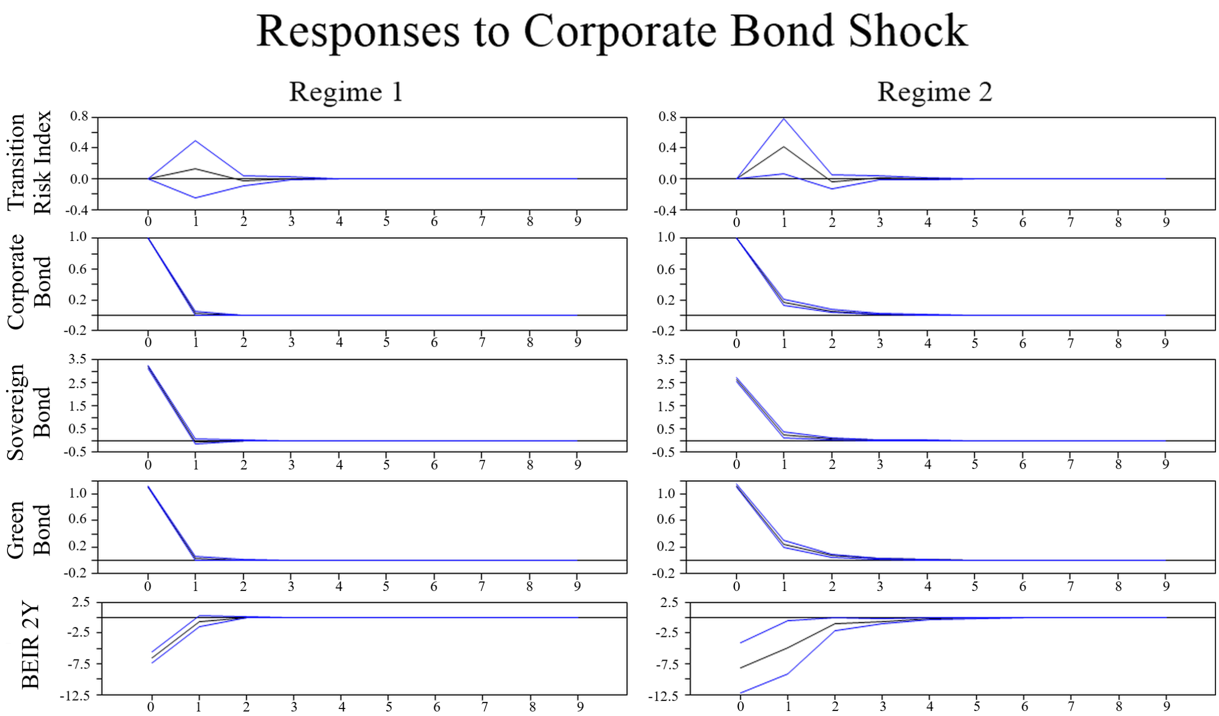


Figure 10: GIRFs illustrating the response of two-year BEIR, the TRI, and bond markets to a corporate bond shock under different volatility regimes. Solid black lines indicate the estimated responses, while blue bands represent 95% confidence intervals.

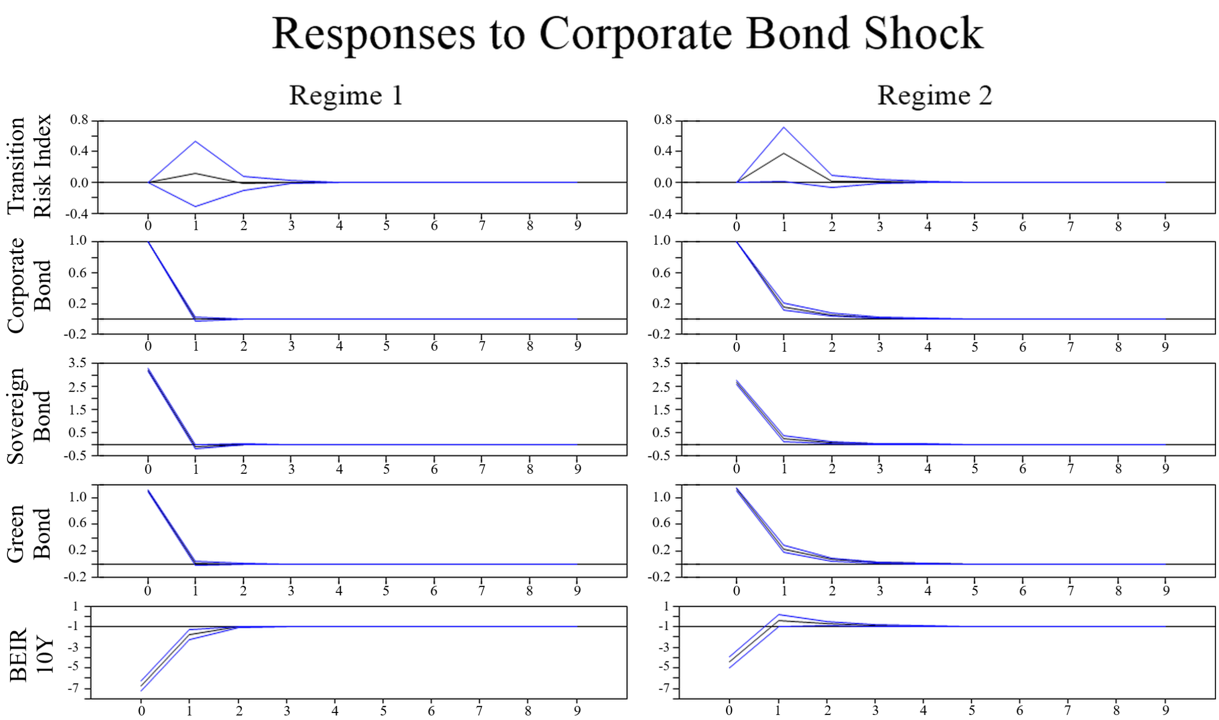


Figure 11: GIRFs illustrating the response of ten-year BEIR, the TRI, and bond markets to a corporate bond shock under different volatility regimes. Solid black lines indicate the estimated responses, while blue bands represent 95% confidence intervals.

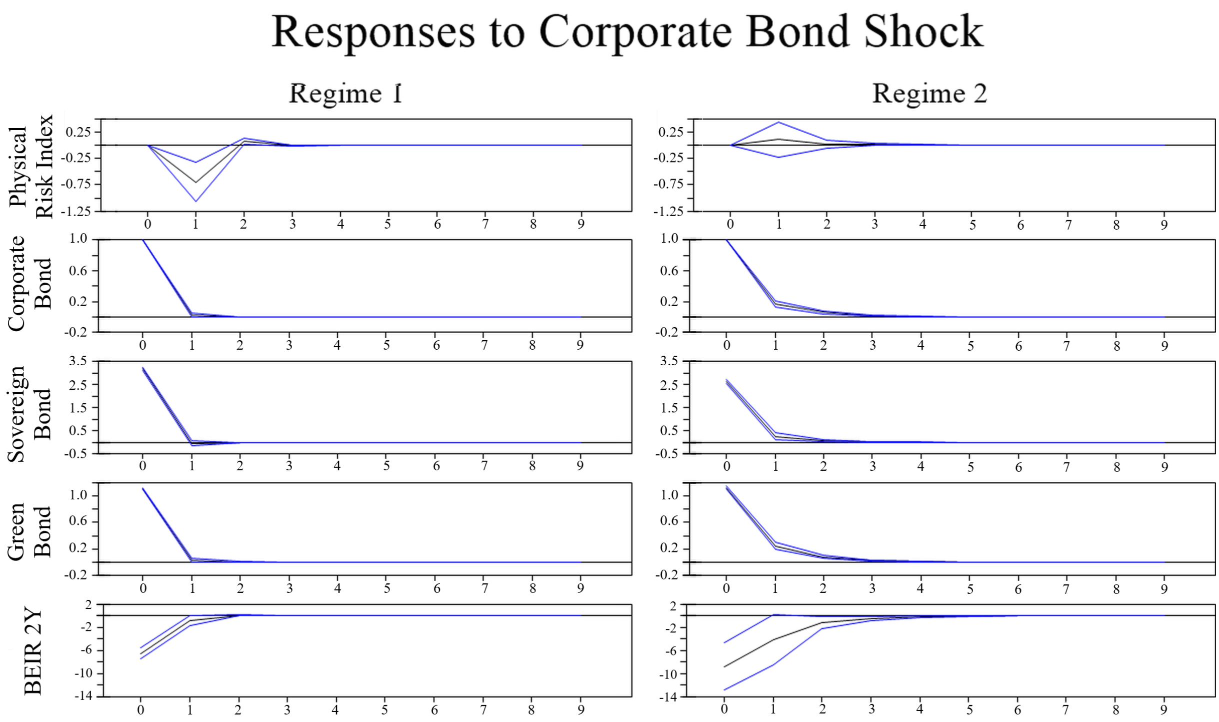


Figure 12: GIRFs illustrating the response of two-year BEIR, the PRI, and bond markets to a corporate bond shock under different volatility regimes. Solid black lines indicate the estimated responses, while blue bands represent 95% confidence intervals.

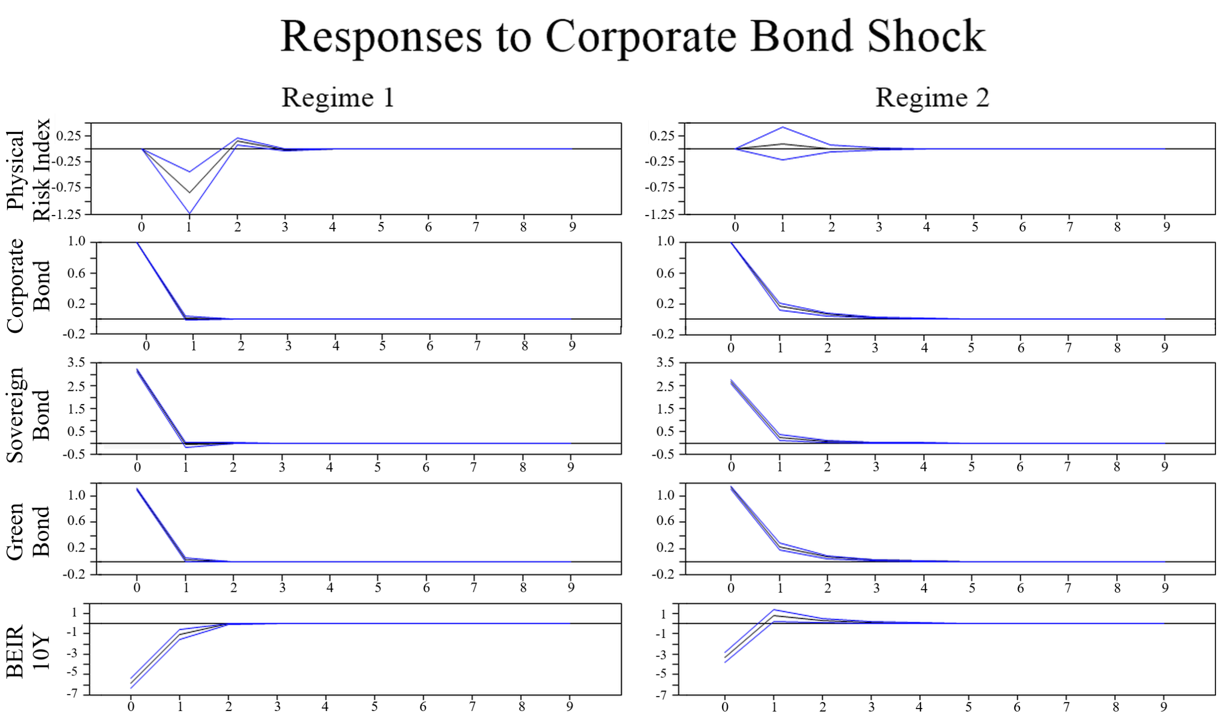


Figure 13: GIRFs illustrating the response of ten-year BEIR, the PRI, and bond markets to a corporate bond shock under different volatility regimes. Solid black lines indicate the estimated responses, while blue bands represent 95% confidence intervals.

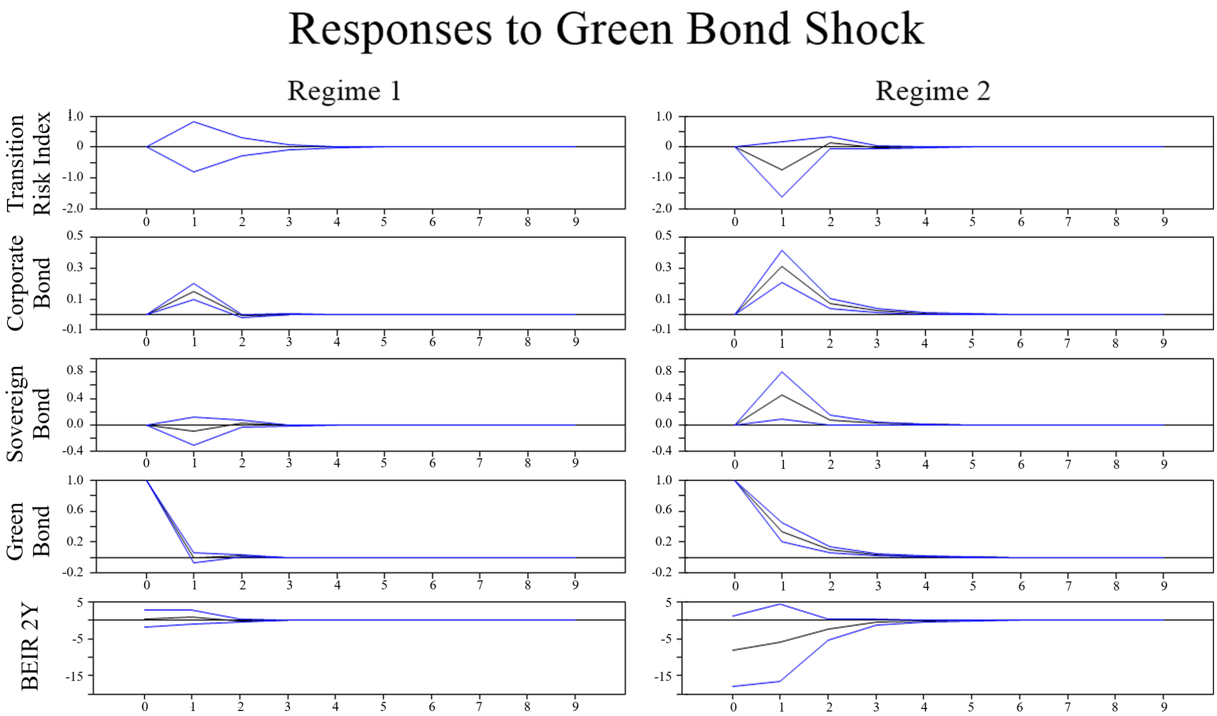


Figure 14: GIRFs showing the impact of an exogenous shock to Green Bonds on two-year BEIR, the TRI, and bond markets. Solid black lines indicate the estimated responses, while blue bands represent 95% confidence intervals.

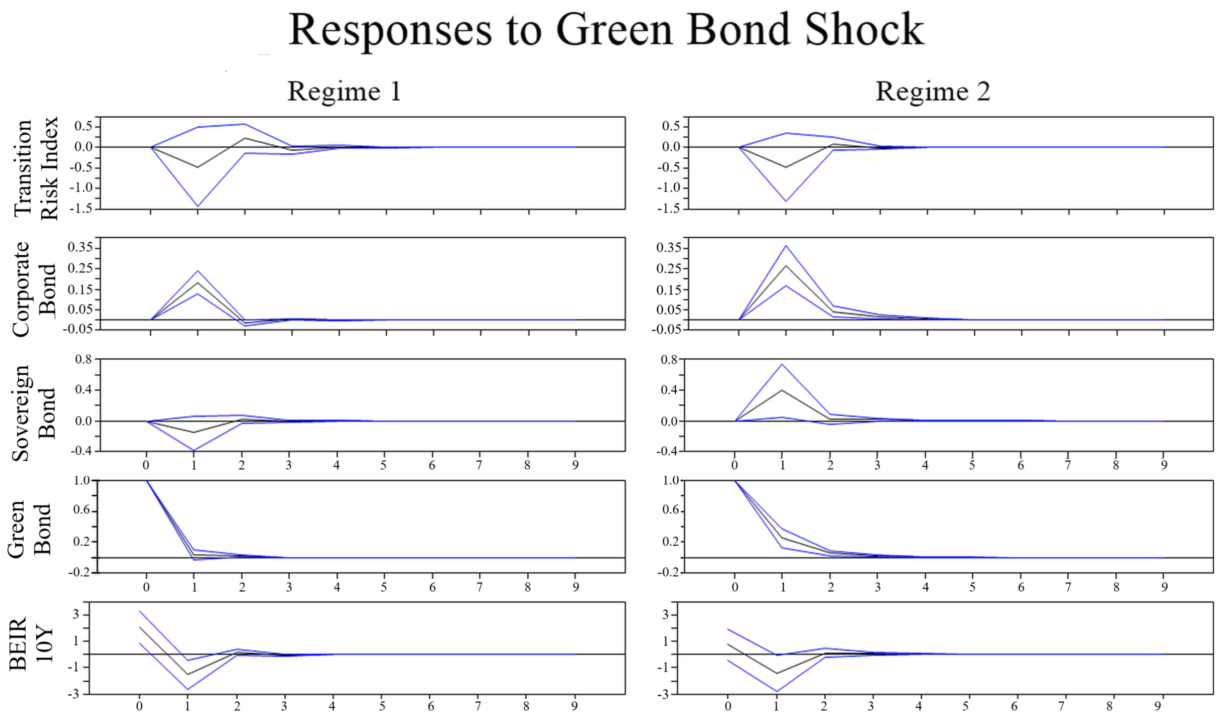


Figure 15: GIRFs showing the impact of an exogenous shock to Green Bonds on ten-year BEIR, the TRI, and bond markets. Solid black lines indicate the estimated responses, while blue bands represent 95% confidence intervals.

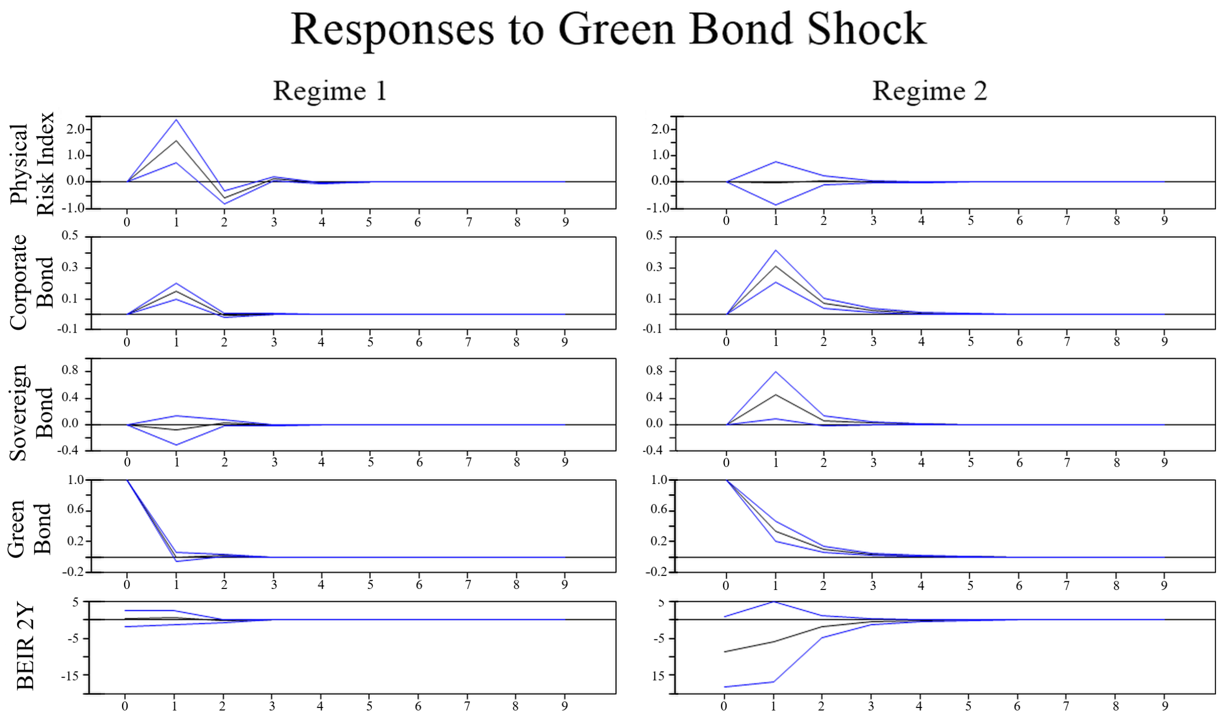


Figure 16: GIRFs showing the impact of an exogenous shock to Green Bonds on two-year BEIR, the PRI, and bond markets. Solid black lines indicate the estimated responses, while blue bands represent 95% confidence intervals.

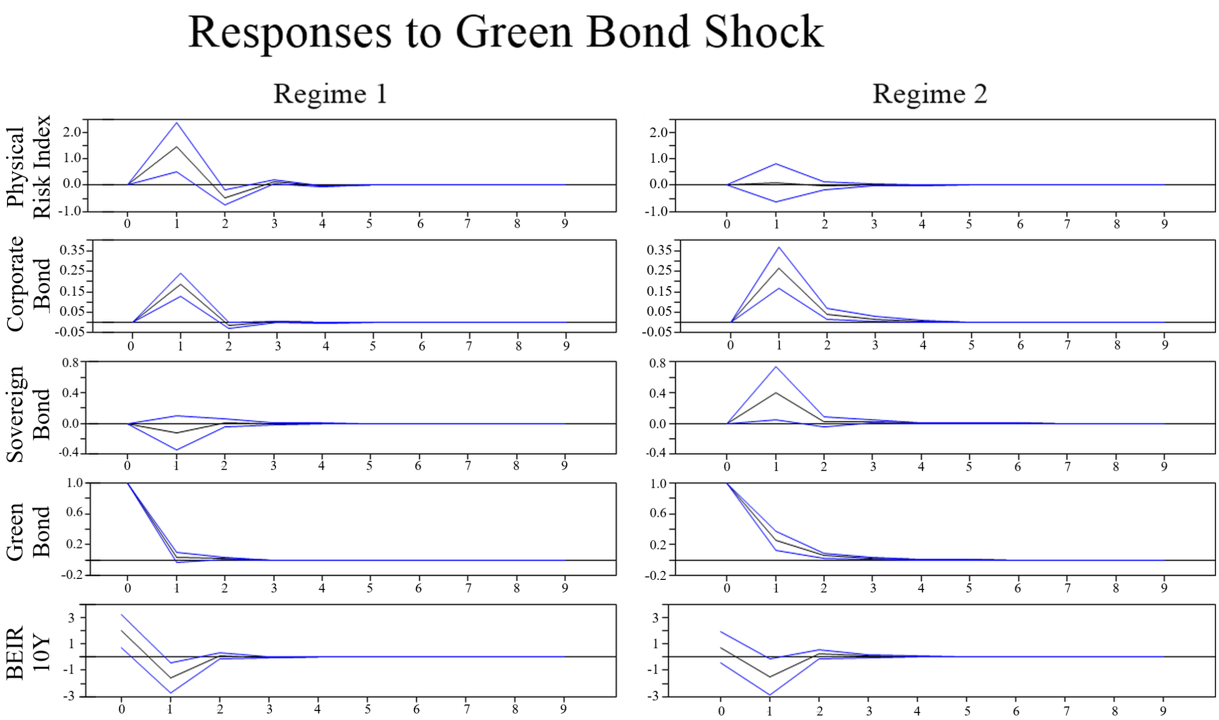


Figure 17: GIRFs showing the impact of an exogenous shock to Green Bonds on ten-year BEIR, the PRI, and bond markets. Solid black lines indicate the estimated responses, while blue bands represent 95% confidence intervals.

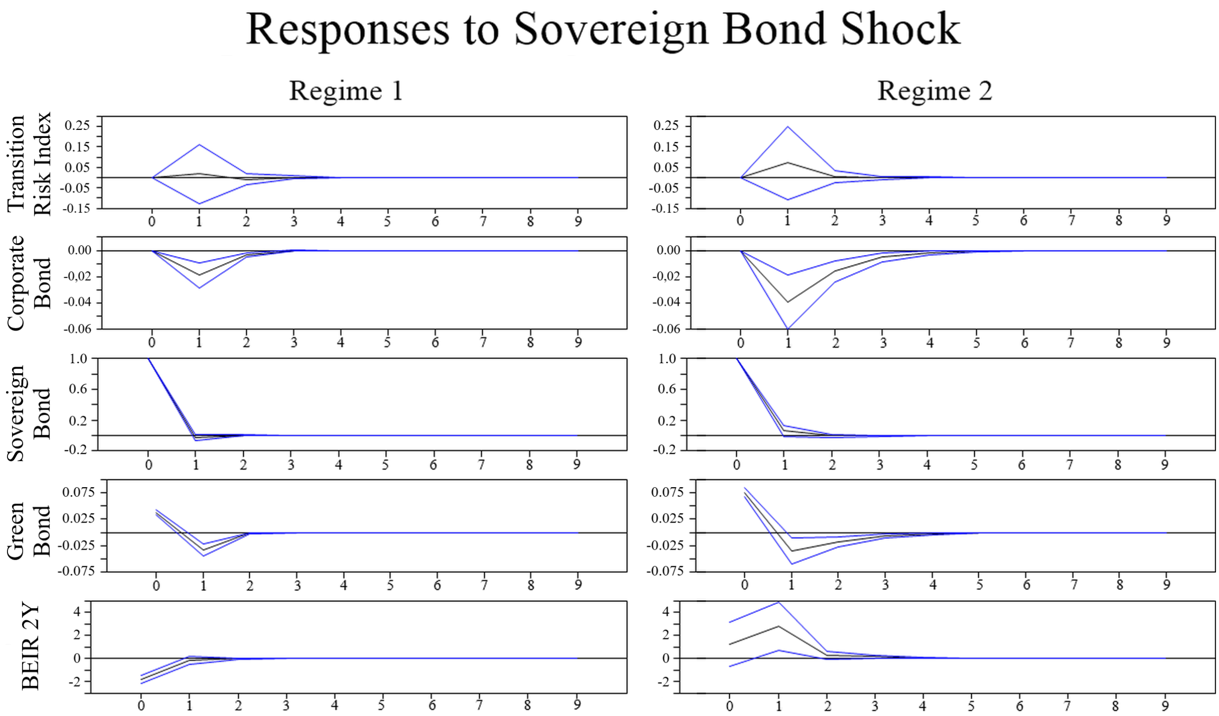


Figure 18: GIRFs displaying the effects of a Sovereign Bond shock on two-year BEIR, the TRI, and bond markets under different volatility regimes. Solid black lines indicate the estimated responses, while blue bands represent 95% confidence intervals.

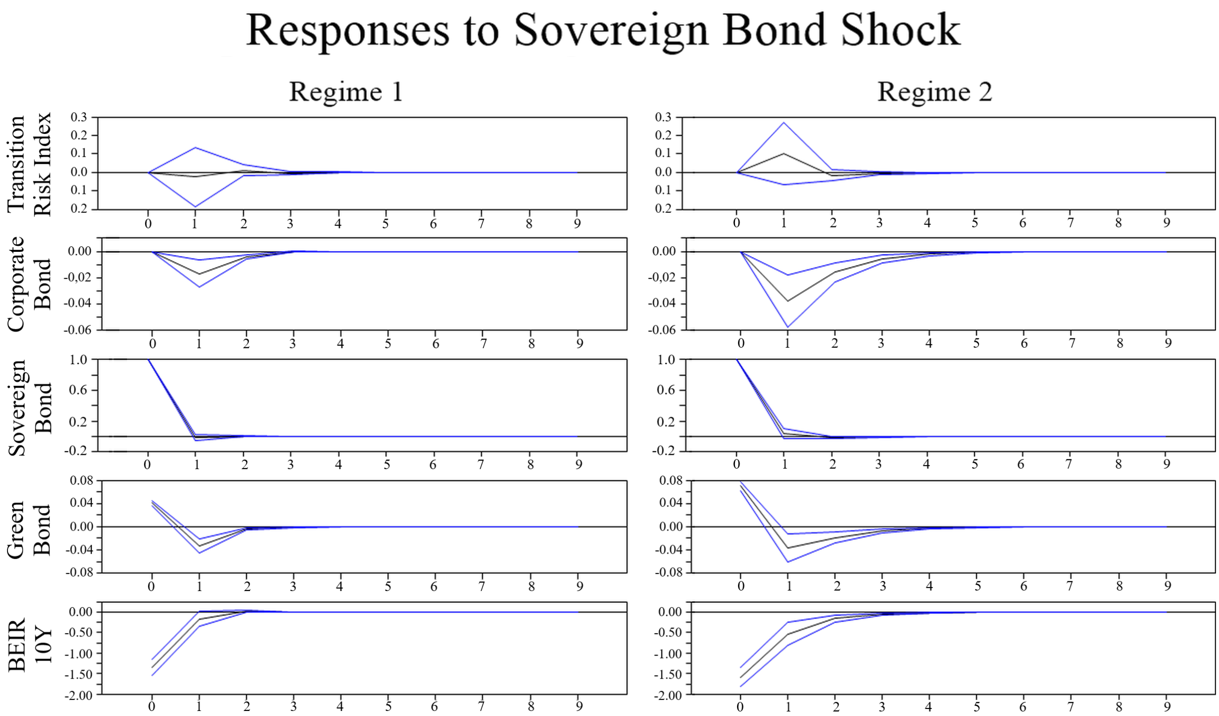


Figure 19: GIRFs displaying the effects of a Sovereign Bond shock on ten-year BEIR, the TRI, and bond markets under different volatility regimes. Solid black lines indicate the estimated responses, while blue bands represent 95% confidence intervals.

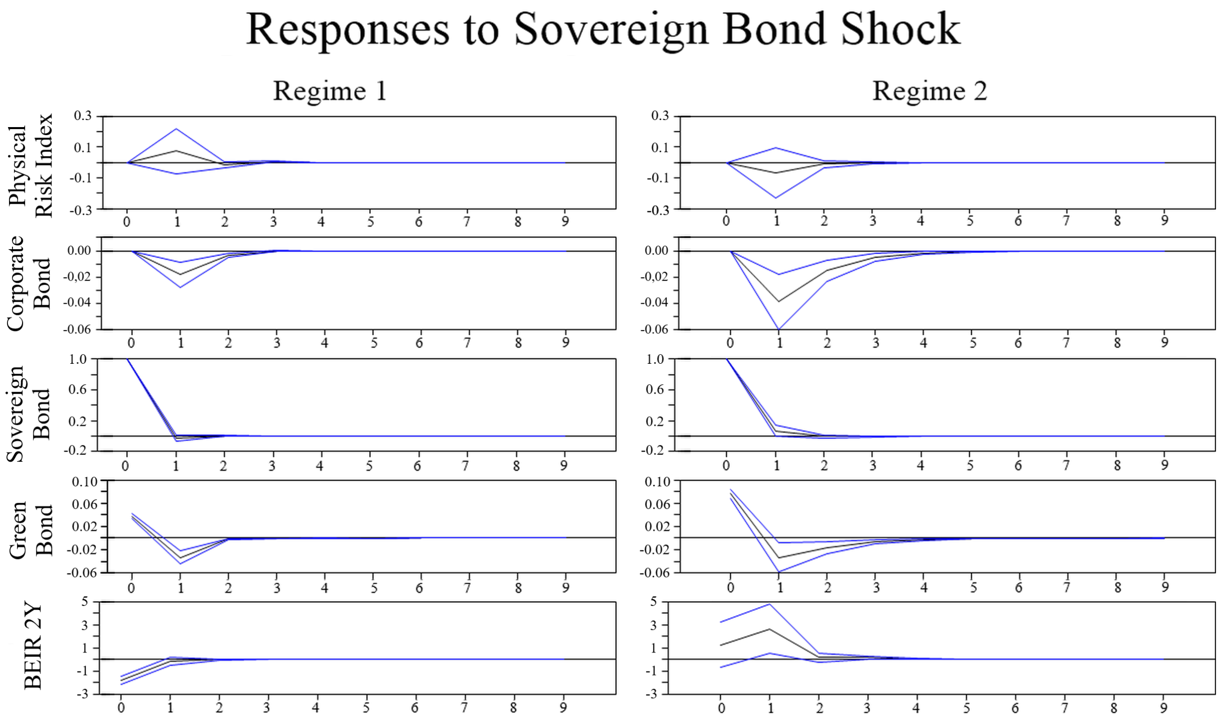


Figure 20: GIRFs displaying the effects of a Sovereign Bond shock on two-year BEIR, the PRI, and bond markets under different volatility regimes. Solid black lines indicate the estimated responses, while blue bands represent 95% confidence intervals.

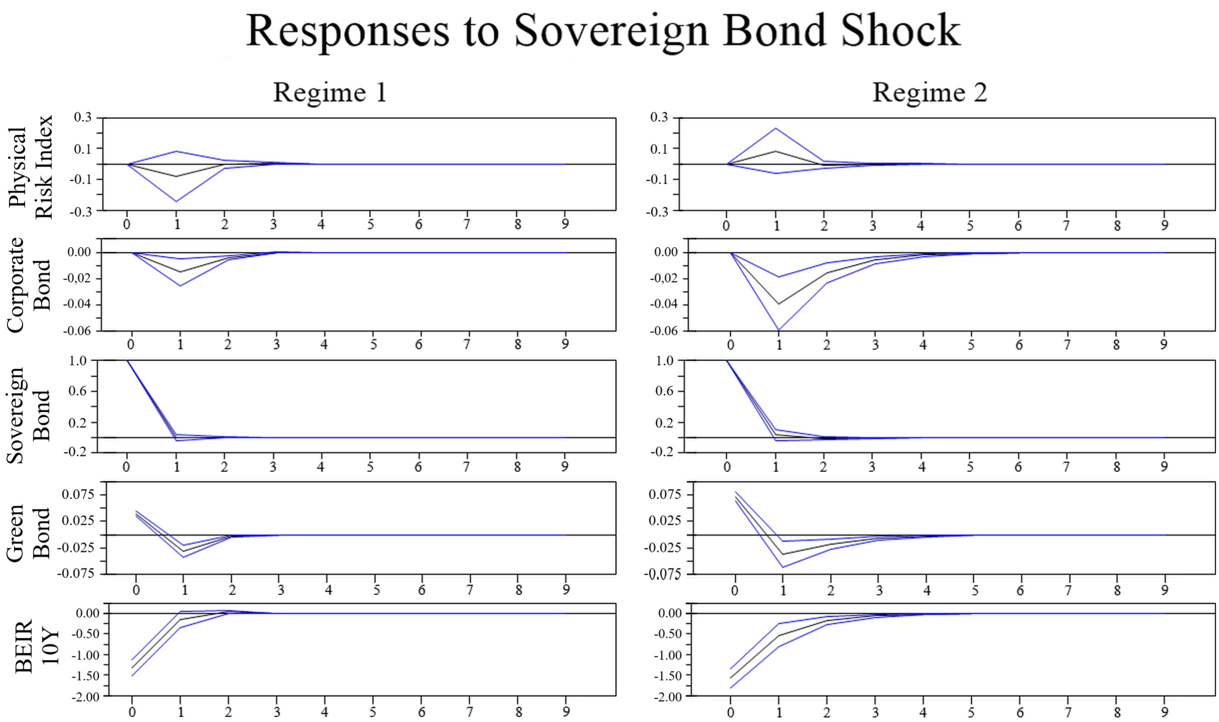


Figure 21: GIRFs displaying the effects of a Sovereign Bond shock on ten-year BEIR, the PRI, and bond markets under different volatility regimes. Solid black lines indicate the estimated responses, while blue bands represent 95% confidence intervals.

Figure 18, 19, 20 and 21 capture the system's dynamic response to a shock to sovereign bonds. In the low volatility regime (Regime 1) sovereign bonds exhibit monotonic convergence at period one. Green bonds respond positively at the time of the shock, followed by a negative reaction before fully converging at period two. Corporate bonds display a negative response at period one. The two- and ten-year BEIR experience a significant negative reaction at the time of the shock with nuanced shock amplification. The TRI and PRI remain insignificant. In the high volatility regime (Regime 2), sovereign bonds behave as in the low volatility regime. Green bonds exhibit a positive reaction at the time of the shock, followed by a negative response at period one. However, they undergo a more prolonged adjustment, with monotonic convergence extending until period four, indicating contagion. Corporate bonds again show a negative response at period one, with a more extended adjustment process, also suggesting contagion. The ten-year BEIR exhibits a significant negative reaction at period one, again showing nuanced shock amplification. In contrast, the two-year BEIR turns significantly positive at period one. The TRI and PRI remain insignificant.

The robustness checks in Figures C.14 to C.25 support the findings, while the evidence for green bonds is weaker and less stable.[12] However, the robust results confirm that green bonds and corporate bonds exhibit the strongest interrelationships, responding similarly to corporate shocks and showing amplified transmission patterns during periods of increased volatility. The divergence between these instruments remains relatively subtle. This is in line with the assessment of European authorities that the taken policy measures facilitate a gradual, structured transition and should not cause sudden disruptions (ECB, 2022).

Our findings indicate that sovereign bonds and corporate bonds exhibit limited interconnectedness, as evidenced by their asymmetric responses to mutual shocks. While an increase in sovereign bonds leads to a decline in corporate bonds across both regimes, a more pronounced high volatility regime, an increase in corporate bonds, in contrast, elicits a positive

[12]This refers to the reaction to green bond shocks and the sovereign and green bond relationship. It is not to be interpreted as a methodological limitation of the MS-VAR model, but rather as a consequence of specific data characteristics. These include the shorter sample period of the control group, evolving index construction standards in the market's early stages, and the subsequent limited availability of consistent time series of adequate length. Furthermore, the lower liquidity and depth of the green bond market also contribute to the difficulty in identifying risk transmission within this segment. We therefore focus our discussion on the results that remain robust across specifications.

response in sovereign bonds, with the crucial distinction that corporate bonds lack safe-haven characteristics.

## 4.5 Regime-Dependent Reduced-Form Coefficients

To complement our GIRF analysis, we examine the MS-VAR's regime-dependent reduced-form coefficients, which offer a parametric view of the system's predictive dynamics. This section reconciles these lagged relationships with the contemporaneous shock responses from the GIRFs. Full coefficient magnitudes and significance levels for the four specifications, pairing (i) TRI or PRI with (ii) either the two-year or ten-year BEIR, are reported in Tables B.2, B.5 and discussed in Appendix B.

The comparison between the MS-VAR coefficients and the GIRFs confirms the conclusion of state dependence: stronger bond–inflation comovement in high volatility regimes (contagion) and weaker, often insignificant, direct climate-to-BEIR loadings (interdependence or decoupling). Methodologically, the coefficients capture predictive relationships of lagged variables ($y_{t-1} \rightarrow y_t$), whereas GIRFs illustrate contemporaneous co-movement under generalised shocks. This distinction explains why coefficient signs sometimes diverge from shock responses. For example, the lagged corporate coefficient in the government equation is negative and significant across regimes (e.g., $-0.024^{**}/-0.061^{***}$ in Spec. 1), reflecting partial mean reversion in sovereign yields and a substitution channel when credit spreads widen. In contrast, a positive corporate bond shock in the GIRFs elicits a positive response in sovereign bonds, indicating contemporaneous contagion. A similar dynamic holds for inflation expectations in that lagged corporate conditions predict higher future BEIRs in high volatility states (e.g., corporate $\rightarrow$ 10Y BEIR: $0.260^{**}$ in Spec. 2), yet an immediate corporate bond shock lowers BEIRs on impact.

These sign divergences, when interpreted through the difference between predictive linkages and shock-based co-movements, show how an immediate, shock-driven contagion can coexist with a predictable, opposing tendency in the subsequent period.

## 4.6 Implications of Findings

We find that climate-related risks have only minor impacts on European bond markets. This likely reflects the relatively small scale of climate-related losses compared to the size of the EU economy, where damages remain limited as a share of GDP despite their large absolute value (European Environment Agency, 2024a).[13] By contrast, countries with higher exposure, such as small island developing states, experience far larger losses relative to output, implying stronger macro-financial transmission channels from physical risk to sovereign risk (International Monetary Fund, 2016; IPCC, 2022). This heterogeneity helps reconcile our muted European results with evidence of stronger effects elsewhere. While we observe little divergence between green and conventional bonds facing TRI shocks, the possibility of a "too late, too sudden" transition cannot be ruled out (Batten et al., 2016; European Systemic Risk Board, 2016). The stronger impact of climate-related risks on short-term rather than long-term inflation expectations suggests that markets either trust the ECB's capacity to contain medium-term inflation or do not yet view climate-risk related shocks as structural drivers of persistent inflation. However, this aggregate finding masks a crucial state-dependency: financial markets price transition risk almost exclusively during periods of low volatility. This state-dependency has an important policy implication related to investor inattention during crises. During low volatility periods, the market functions as an efficient signal processor where market-based policies effectively reprice risk, triggering potentially a carbon divestment effect. In sharp contrast, during high volatility periods, dominant systemic risk signals saturate the market's attention; consequently, the signal from the same climate policy is overshadowed by the salience of systemic risk and fails to be incorporated into asset prices. This might imply that policies are less effective when the system is stressed. While a full normative analysis is beyond the scope of this paper, our results support a non-delaying, proactive transition policy strategy to avoid policy efficacy losses by dealing with multiple problems in society all at once.

While we cannot directly identify the underlying causes of exogenous shocks to inflation

[13]For EU-wide events in 2025, short-run losses are estimated at about 0.26% of GDP (Usman et al., 2025), whereas SIDS commonly register annual damages near 2% of GDP on average and occasionally above 30% in single events (International Monetary Fund, 2016; IPCC, 2022). Recent UNDP estimates further suggest that SIDS experience disaster losses around seven times higher than other countries as a share of GDP (United Nations Development Programme, 2024).

expectations, insights from the literature, the characteristics of high volatility regimes, and the observed effect directions allow us to infer that the short-term BEIR shocks are rather supply-driven and long-term inflation expectation shocks are likely to be demand-driven. Against this backdrop, long-term inflation shocks driven by climate-related risks are likely to have a negative impact on bond markets. This scenario has not unfolded yet, but it warrants careful and ongoing scrutiny particularly, as in high volatility regimes markets tend to overreact to shocks, a pattern also reflected in our findings. As climate-related risks become more persistent, the challenge for central banks in balancing the credibility of their long-term inflation target with financial stability considerations becomes increasingly complex. Our findings, particularly the observed dynamics in high volatility regimes, highlight that such a scenario could necessitate a carefully considered policy stance. This inherent trade-off, where monetary authorities might need to adopt a cautiously hawkish approach while mitigating financial market destabilisation, is well-documented in the literature (Bandera et al., 2023; Boissay et al., 2023; Chavleishvili et al., 2023). The robustness of our findings is reinforced by their consistency across model specifications with different datasets. However, for effective risk governance it is essential to recognise that backward-looking statistical approaches may fail to fully capture evolving risk drivers (Charpentier, 2008). And as climate-related risks increase, continuous monitoring of emerging developments is and will be crucial.

While our current statistical framework identifies regime-dependent responses, it does not directly model central bank reaction functions or specific monetary policy instruments. However, even without explicit reaction functions or direct modelling of policy instruments, our regime-switching analysis provides crucial insights into how climate-related risks can amplify financial linkages and affect inflation expectations under different market conditions, thereby remaining highly relevant for central banks' ongoing monitoring of financial stability under climate-related shocks. Future research could extend this analysis by explicitly incorporating short-term interest rates, policy rates, or indicators derived from central bank communication (for example ECB announcements) to empirically test their interaction with climate-related risks and inflation expectations within an extended model specification; this could build on frameworks that model central bank reactions to inflation shocks (for example the seminal work on policy rules by Taylor (1993)) and on recent approaches considering the specific challenges of “greenflation” and “climateflation” for monetary policy (for example Schnabel, 2022a,b, Lane, 2022). We also acknowledge that our MS-VAR framework is not designed to explicitly estimate credit spreads, duration risk (or specific maturity risk controls), or model risk premia; standard methodologies used for these estimates (e.g. term structure models) either do not inherently support the regime-dependent dynamics central to our findings, or integrating them would constitute a separate, substantial methodological contribution beyond the scope of this paper. For more direct insights into underlying causal mechanisms, future research could investigate specific transmission channels of climate-related risks, such as the explicit role of yield-curve shifts or credit-risk repricing, by applying structural identification or advanced causality-based approaches (for example using structural VAR models or alternative causality tests) as a complement to our statistical framework. Extending the analysis to granular bond-level data would also allow explicit control of individual security liquidity, specific maturities, and issuer characteristics (for example firm-specific climate risk exposures, credit ratings), thereby refining insights into how climate risk impacts different bond segments. As the green bond market matures and liquidity improves, we expect these structural transmission channels to become clearer. From a policy perspective, this suggests that conventional markets currently provide more reliable signals for monitoring climate-related risk, while the role of green bonds as an indicator will strengthen over time as the market develops; in this vein, Malovaná and Frait (2017) emphasise the importance of close cooperation and coordination between monetary and macroprudential policymakers.

# 5 Concluding Remarks

This study provides novel empirical evidence on how climate-related risks affect inflation expectations and bond markets in Europe through regime-dependent transmission mechanisms. Using a MS-VAR with European news-based transition and physical risk indices and GIRFs, our findings highlight the role of climate-related risk in shaping market linkages and stability.

Transition risks exert only limited effects, modestly dampening short-term inflation expectations in calm markets without materially impacting bond prices. Physical risks, however, depress bond returns and raise short-term inflation expectations under stress, suggesting that extreme events can amplify volatility and place temporary upward pressure on expectations. Long-term inflation expectations remain stable, indicating continued credibility of the ECB's target. We also find that shocks to short-term expectations and to corporate bonds propagate more strongly across bond classes in high volatility states, while green and conventional bonds do not materially diverge under stress, implying little evidence of abrupt capital reallocation.

These results suggest potential importance for both monetary and financial stability assessments to consider climate-related risk shocks and regime-dependent volatility when evaluating inflation dynamics, expected risk premia (via BEIRs), and systemic risk. For investors, the evidence points to the growing relevance of climate-aware asset allocation and stress testing, as climate-related shocks can alter correlations and increase systemic exposure during turbulent periods.

Findings are robust across alternative specifications and identification checks (see Appendix), though limitations remain regarding the measurement precision of news-based climate risk indices and regime classification. Future research could extend this analysis by examining cross-market spillovers, interactions with regulatory disclosure frameworks, and the evolving role of climate risk in shaping European capital market integration.

Overall, our results indicate that climate-related risks are transmitted through the inflation channel and interact with bond market dynamics in regime-dependent ways. This finding suggests avenues for potentially more active integration of climate-related risk considerations into macroprudential frameworks, monetary policy analyses, and portfolio risk management strategies, thereby informing future discussions on financial stability in European markets.

# A Data Details and Descriptive Statistics

Table A.1 provides the descriptive statistics for all financial and risk indices used in the analysis, including measures of central tendency, dispersion, and distributional characteristics.

Table A.1: Descriptive statistics for the Key Financial Indices

| Data | Mean | Median | Std. Dev. | Min | Max | Skewness | Kurtosis |
|---|---|---|---|---|---|---|---|
| TRI | -0.0029 | -0.0047 | 0.0216 | -0.0815 | 0.1380 | 0.6214 | 2.3682 |
| PRI | -0.0017 | -0.0040 | 0.0207 | -0.0631 | 0.1225 | 0.8045 | 1.9147 |
| Corporate Bonds | 0.0000 | 0.0001 | 0.0019 | -0.0196 | 0.0129 | -0.4743 | 10.4251 |
| Green Bonds | 0.0000 | 0.0002 | 0.0067 | -0.0358 | 0.0376 | 0.0123 | 3.0600 |
| Sovereign Bonds | 0.0001 | 0.0001 | 0.0023 | -0.0242 | 0.0144 | -0.8010 | 9.9208 |
| Two-year BEIR | -0.0059 | 0.0010 | 0.1626 | -0.7631 | 0.7358 | -0.3723 | 11.5122 |
| Ten-year BEIR | 0.0002 | 0.0010 | 0.0290 | -0.0800 | 0.0800 | -0.0795 | 0.6782 |

Notes: TRI = Transition Risk Index, PRI = Physical Risk Index, BEIR = Breakeven Inflation Rate. Std. Dev. = Standard Deviation, Min = Minimum, Max = Maximum. The sample period spans from October 20, 2014, to June 24, 2024.

Figure A.1 presents the time series dynamics of the six key variables. The plot illustrates the response of financial market variables to major external shocks, such as the COVID-19 pandemic (2020) and the period of heightened geopolitical risk (since 2022), which are particularly evident in the two-year BEIR and bond markets. The longer-term BEIR shows the expected greater resilience. Spikes in the climate-related risk indices coincide with unexpected high-impact news discussions concerning these risks.

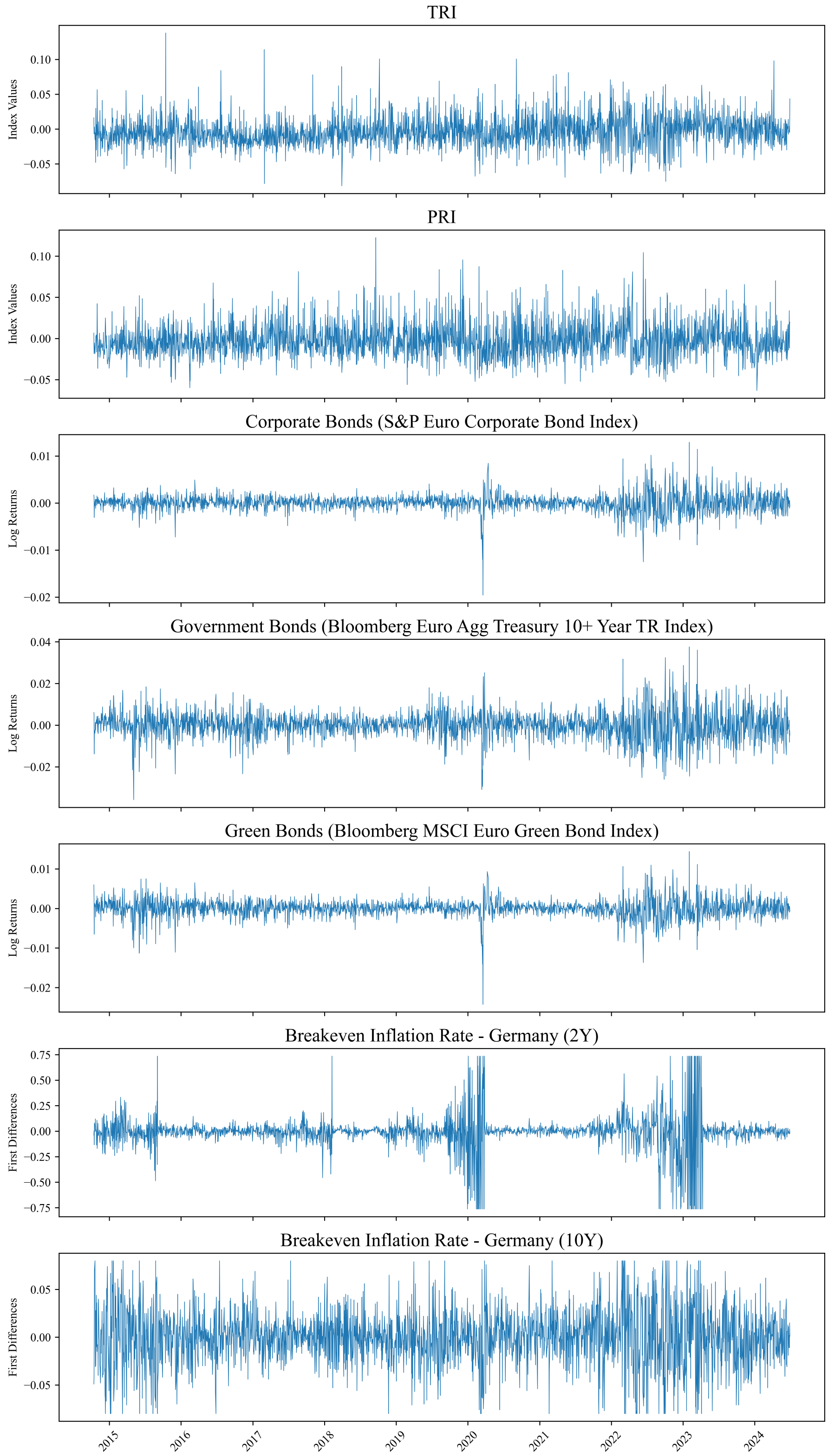


Figure A.1: Time series of climate-related risks, bond returns, and breakeven inflation rates.

Notes: This figure displays TRI, PRI, corporate bond returns (S&P Euro Corporate Bond Index), government bond returns (Bloomberg Euro Agg Treasury 10+ Year TR Index), green bond returns (Bloomberg MSCI Euro Green Bond Index), and first differences of the German breakeven inflation rates (2Y and 10Y). Data are adjusted using 99% winsorisation to control for extreme outliers.

# B Regime-Dependent Reduced-Form Coefficients

This appendix documents the regime-dependent MS-VAR coefficients and the associated regularities discussed in Section 4.

Overall, three regularities emerge. First, corporate bonds exhibit a materially negative loading on climate risk: the TRI–corporate coefficient is significantly negative in the low volatility regime ($-0.187^{***}$ in Spec. 1; $-0.199^{***}$ in Spec. 2), while under PRI the corporate exposure is significantly negative in both regimes ($-0.126^{***}$, $-0.116^{**}$ in Spec. 3 and $-0.132^{***}$, $-0.113^{**}$ in Spec. 4). This pattern suggests that physical risk is priced even in turbulent states, whereas transition risk is priced mainly in calm states. Second, we find a stable cross-asset spillover from corporate to sovereign bonds: the lagged corporate coefficient in the government equation is negative and significant in both regimes (e.g., $-0.024^{**}$/$-0.061^{***}$ in Spec. 1, $-0.021^{*}$/$-0.044^{**}$ in Spec. 2), consistent with partial mean reversion in sovereign yields (negative own-lag) and a substitution channel when credit spreads widen. Third, linkages to inflation expectations are state dependent: BEIR responds positively to corporate conditions—strongly so in high volatility states and when using the 10-year horizon (e.g., corporate $\rightarrow$ 10Y BEIR: $0.260^{***}$ in Spec. 2; green $\rightarrow$ 10Y BEIR: $3.332^{**}$ in Spec. 2 and $3.534^{**}$ in Spec. 4), and the government $\rightarrow$ 2Y BEIR coefficient is positive in high volatility regimes (e.g., $0.322^{**}$ in Spec. 1; $0.324^{**}$ in Spec. 3; $0.248^{**}$ in Spec. 4). In contrast, the TRI and PRI coefficients in the BEIR equations are generally small and imprecise, indicating that climate risk affects inflation expectations primarily indirectly—through its impact on bond market conditions—rather than through a direct reduced-form channel.

Table B.2: MS-VAR(1) Coefficients by Regime (Specification 1 = TRI + 2-year BEIR)

| **Regressor** | **Regime 1: Low volatility** | **Regime 2: High volatility** |
|---|---|---|
| **Panel A: Dependent variable = Corporate bond** | | |
| Transition risk | $-0.187^{***}$ (0.023) | $-0.075$ (0.047) |
| Corporate bond | $-0.000$ (0.001) | $-0.003$ (0.005) |
| Green bond | $-0.001$ (0.006) | $-0.012$ (0.018) |
| Government bond | 0.000 (0.002) | $-0.004$ (0.007) |
| 2-year BEIR | 0.057 (0.052) | 0.641 (0.533) |
| **Panel B: Dependent variable = Green bond** | | |
| Transition risk | 0.069 (0.982) | 0.948 (1.036) |
| Corporate bond | $-0.061$ (0.066) | $-0.020$ (0.122) |
| Green bond | 0.126 (0.274) | $-0.330$ (0.415) |
| Government bond | $0.142^{*}$ (0.078) | 0.030 (0.148) |
| 2-year BEIR | $-1.028$ (2.345) | $-7.375$ (12.098) |
| **Panel C: Dependent variable = Government bond** | | |
| Transition risk | 0.039 (0.150) | 0.117 (0.190) |
| Corporate bond | $-0.024^{**}$ (0.010) | $-0.061^{***}$ (0.022) |
| Green bond | $-0.023$ (0.039) | 0.033 (0.076) |
| Government bond | $-0.032^{***}$ (0.011) | $-0.058^{**}$ (0.027) |
| 2-year BEIR | $-0.251$ (0.353) | 3.586 (2.229) |
| **Panel D: Dependent variable = 2-year BEIR** | | |
| Transition risk | 0.007 (0.824) | $-0.708$ (0.909) |
| Corporate bond | $0.150^{***}$ (0.052) | $0.307^{***}$ (0.106) |
| Green bond | $-0.089$ (0.215) | 0.423 (0.359) |
| Government bond | $-0.005$ (0.063) | $0.322^{**}$ (0.130) |
| 2-year BEIR | 0.954 (1.919) | $-7.440$ (10.493) |

**Notes:** Coefficient estimates from a Markov-switching VAR(1) estimated on a five-dimensional system comprising TRI, corporate bonds, sovereign bonds, green bonds, and the 2-year BEIR. Lag order was chosen by the Hannan–Quinn Information Criterion (HQIC); only the first lag is reported. Reported values are regime-dependent coefficients with standard errors in parentheses. Regime 1 corresponds to the low volatility state; Regime 2 to the high volatility state. $^{*}$, $^{**}$, and $^{***}$ denote significance at the 10%, 5%, and 1% levels, respectively.

Table B.3: MS-VAR(1) Coefficients by Regime (Specification 2: TRI + 10-year BEIR)

| **Regressor** | **Regime 1: Low volatility** | **Regime 2: High volatility** |
|---|---|---|
| **Panel A: Dependent variable = Corporate bond** | | |
| Transition risk | $-0.199^{***}$ (0.024) | $-0.062$ (0.046) |
| Corporate bond | $-0.000$ (0.001) | $-0.002$ (0.005) |
| Green bond | $-0.111^{*}$ (0.067) | 0.014 (0.115) |
| Government bond | $-0.021^{*}$ (0.011) | $-0.044^{**}$ (0.021) |
| 10-year BEIR | $0.177^{***}$ (0.056) | $0.260^{***}$ (0.099) |
| **Panel B: Dependent variable = Green bond** | | |
| Transition risk | 0.589 (1.121) | 0.534 (0.973) |
| Corporate bond | $-0.111^{*}$ (0.067) | 0.014 (0.115) |
| Green bond | 0.074 (0.273) | $-0.234$ (0.398) |
| Government bond | 0.098 (0.080) | 0.087 (0.140) |
| 10-year BEIR | $-0.150$ (0.225) | 0.380 (0.339) |
| **Panel C: Dependent variable = Government bond** | | |
| Transition risk | $-0.023$ (0.173) | 0.171 (0.185) |
| Corporate bond | $-0.021^{*}$ (0.011) | $-0.044^{**}$ (0.021) |
| Green bond | 0.098 (0.080) | 0.087 (0.140) |
| Government bond | $-0.031^{**}$ (0.013) | $-0.040$ (0.026) |
| 10-year BEIR | 0.027 (0.067) | $0.246^{**}$ (0.121) |
| **Panel D: Dependent variable = 10-year BEIR** | | |
| Transition risk | $-0.429$ (0.949) | $-0.484$ (0.825) |
| Corporate bond | $-0.014$ (0.027) | 0.113 (0.074) |
| Green bond | 1.175 (1.334) | $3.332^{**}$ (1.576) |
| Government bond | $-0.117$ (0.202) | $-0.137$ (0.300) |
| 10-year BEIR | $-1.472$ (1.129) | $-1.561$ (1.361) |

**Notes:** Coefficient estimates from a Markov-switching VAR(1) estimated on a five-dimensional system comprising TRI, corporate bonds, sovereign bonds, green bonds, and the 10-year BEIR. Lag order was chosen by the Hannan–Quinn Information Criterion (HQIC); only the first lag is reported. Reported values are regime-dependent coefficients with standard errors in parentheses. Regime 1 corresponds to the low volatility state; Regime 2 to the high volatility state. *, **, and *** denote significance at the 10%, 5%, and 1% levels, respectively.

Table B.4: MS-VAR(1) Coefficients by Regime (Specification 3: PRI + 2-year BEIR)

| **Regressor** | **Regime 1: Low volatility** | **Regime 2: High volatility** |
|---|---|---|
| **Panel A: Dependent variable = Corporate bond** | | |
| Physical risk | $-0.126^{***}$ (0.024) | $-0.116^{**}$ (0.046) |
| Corporate bond | 0.002 (0.002) | 0.003 (0.006) |
| Green bond | $-0.067$ (0.065) | $-0.022$ (0.122) |
| Government bond | $-0.023^{**}$ (0.010) | $-0.061^{***}$ (0.022) |
| 2-year BEIR | $0.154^{***}$ (0.052) | $0.309^{***}$ (0.105) |
| **Panel B: Dependent variable = Green bond** | | |
| Physical risk | $-2.478^{**}$ (0.980) | 0.330 (0.937) |
| Corporate bond | $-0.067$ (0.065) | $-0.022$ (0.122) |
| Green bond | 0.110 (0.271) | $-0.332$ (0.416) |
| Government bond | $0.136^{*}$ (0.077) | 0.025 (0.149) |
| 2-year BEIR | $-0.076$ (0.217) | 0.425 (0.359) |
| **Panel C: Dependent variable = Government bond** | | |
| Physical risk | 0.009 (0.155) | $-0.057$ (0.177) |
| Corporate bond | $-0.023^{**}$ (0.010) | $-0.061^{***}$ (0.022) |
| Green bond | $0.136^{*}$ (0.077) | 0.025 (0.149) |
| Government bond | $-0.032^{***}$ (0.011) | $-0.057^{**}$ (0.027) |
| 2-year BEIR | 0.001 (0.064) | $0.324^{**}$ (0.130) |
| **Panel D: Dependent variable = 2-year BEIR** | | |
| Physical risk | $1.548^{*}$ (0.793) | $-0.063$ (0.821) |
| Corporate bond | $-0.051$ (0.056) | $1.215^{**}$ (0.571) |
| Green bond | $-1.086$ (2.294) | $-6.372$ (12.260) |
| Government bond | $-0.204$ (0.355) | 3.428 (2.268) |
| 2-year BEIR | 0.596 (1.903) | $-7.356$ (10.695) |

**Notes:** Coefficient estimates from a Markov-switching VAR(1) estimated on a five-dimensional system comprising PRI, corporate bonds, sovereign bonds, green bonds, and the 2-year BEIR. Lag order was chosen by the Hannan–Quinn Information Criterion (HQIC); only the first lag is reported. Reported values are regime-dependent coefficients with standard errors in parentheses. Regime 1 corresponds to the low volatility state; Regime 2 to the high volatility state. *, **, and *** denote significance at the 10%, 5%, and 1% levels, respectively.

Table B.5: MS-VAR(1) Coefficients by Regime (Specification 4: PRI + 10-year BEIR)

| **Regressor** | **Regime 1: Low volatility** | **Regime 2: High volatility** |
|---|---|---|
| **Panel A: Dependent variable = Corporate bond** | | |
| Physical risk | $-0.132^{***}$ (0.025) | $-0.113^{**}$ (0.045) |
| Corporate bond | 0.001 (0.001) | 0.005 (0.006) |
| Green bond | $-0.111^{*}$ (0.067) | 0.017 (0.116) |
| Government bond | $-0.020^{*}$ (0.011) | $-0.046^{**}$ (0.022) |
| 10-year BEIR | $0.179^{***}$ (0.055) | $0.263^{***}$ (0.100) |
| **Panel B: Dependent variable = Green bond** | | |
| Physical risk | $-2.042^{*}$ (1.107) | $-0.205$ (0.837) |
| Corporate bond | $-0.111^{*}$ (0.067) | 0.017 (0.116) |
| Green bond | 0.061 (0.270) | $-0.214$ (0.400) |
| Government bond | $-0.001$ (0.043) | 0.092 (0.142) |
| 10-year BEIR | $-0.128$ (0.221) | 0.380 (0.345) |
| **Panel C: Dependent variable = Government bond** | | |
| Physical risk | $-0.166$ (0.174) | 0.103 (0.160) |
| Corporate bond | $-0.020^{*}$ (0.011) | $-0.046^{**}$ (0.022) |
| Green bond | 0.097 (0.079) | 0.092 (0.142) |
| Government bond | $-0.029^{**}$ (0.012) | $-0.041$ (0.027) |
| 10-year BEIR | 0.032 (0.066) | $0.248^{**}$ (0.123) |
| **Panel D: Dependent variable = 10-year BEIR** | | |
| Physical risk | 1.484 (0.928) | 0.064 (0.724) |
| Corporate bond | $-0.026$ (0.028) | 0.031 (0.082) |
| Green bond | 0.971 (1.326) | $3.534^{**}$ (1.591) |
| Government bond | $-0.094$ (0.207) | $-0.142$ (0.303) |
| 10-year BEIR | $-1.575$ (1.115) | $-1.595$ (1.361) |

**Notes:** Coefficient estimates from a Markov-switching VAR(1) estimated on a five-dimensional system comprising PRI, corporate bonds, sovereign bonds, green bonds, and the 10-year BEIR. Lag order was chosen by the Hannan–Quinn Information Criterion (HQIC); only the first lag is reported. Reported values are regime-dependent coefficients with standard errors in parentheses. Regime 1 corresponds to the low volatility state; Regime 2 to the high volatility state. *, **, and *** denote significance at the 10%, 5%, and 1% levels, respectively.

# C Robustness Checks: Alternative Dataset

This appendix reports robustness checks using a second dataset covering the period from 2021-02-23 to 2024-06-28. The main estimation is replicated for the identical sample. Both the regime classification and most estimated relations among the time series remain stable. The dataset includes the following variables: climate-related risks (TRI and PRI), Corporate Bonds (Bloomberg Euro Corporate Bond Index), Green Bonds (Bloomberg MSCI EUR Corporate and Agency Green Bond Index), Government Bonds (ICE BofA Euro Government Index), and BEIRs (Germany 2Y and 10Y). As in the main analysis, the robustness checks are conducted by alternating between the risk indices TRI and PRI and between the breakeven inflation rates of 2 and 10 years, resulting in the corresponding specifications.

## C.1 Regime classifications and Generalized Impulse Response Functions

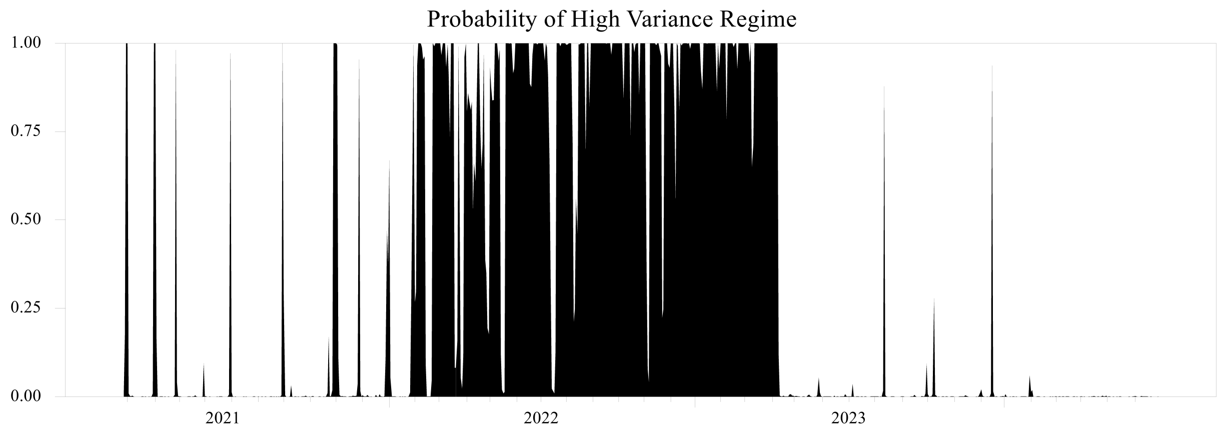


Figure C.2: Specification 5, PRI, BEIR 2Y.

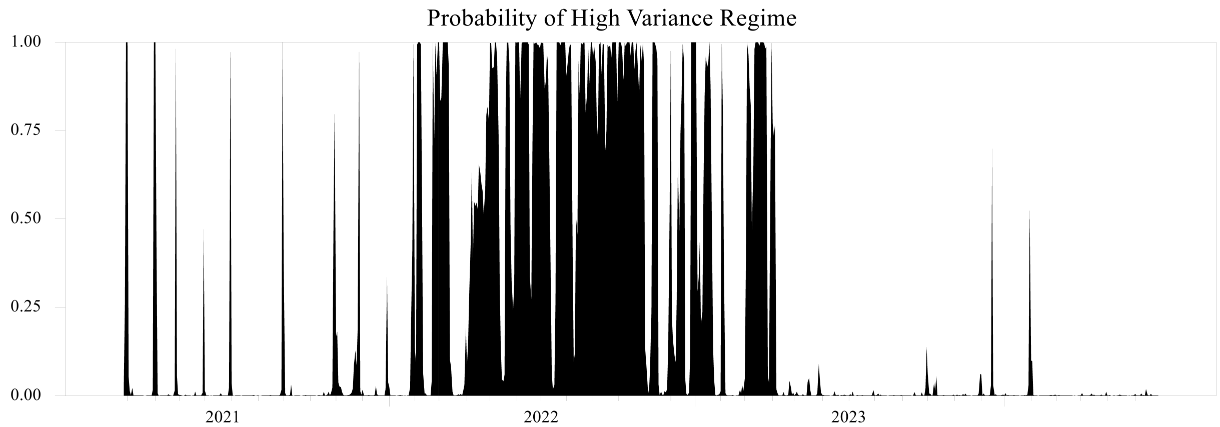


Figure C.3: Specification 6, PRI, BEIR 10Y.

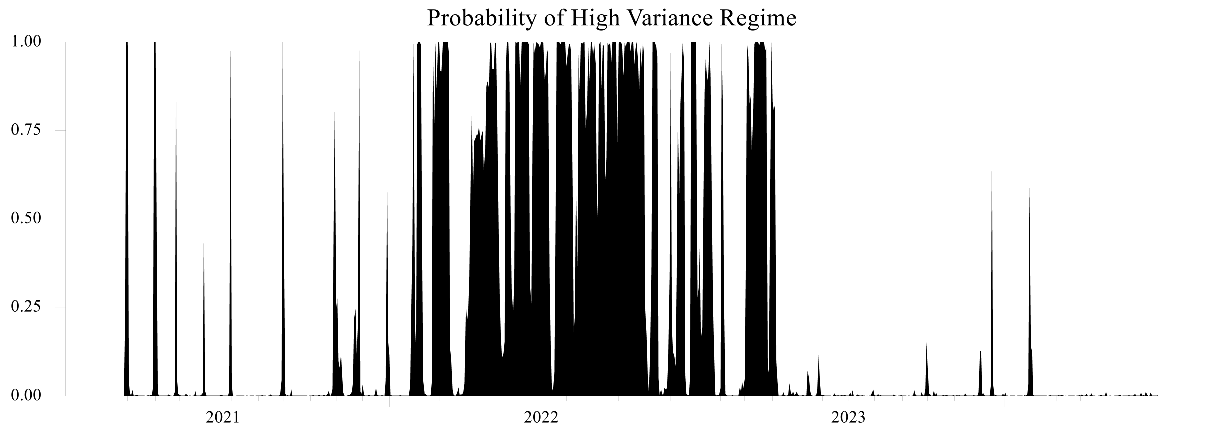


Figure C.4: Specification 7, TRI, BEIR 10Y.

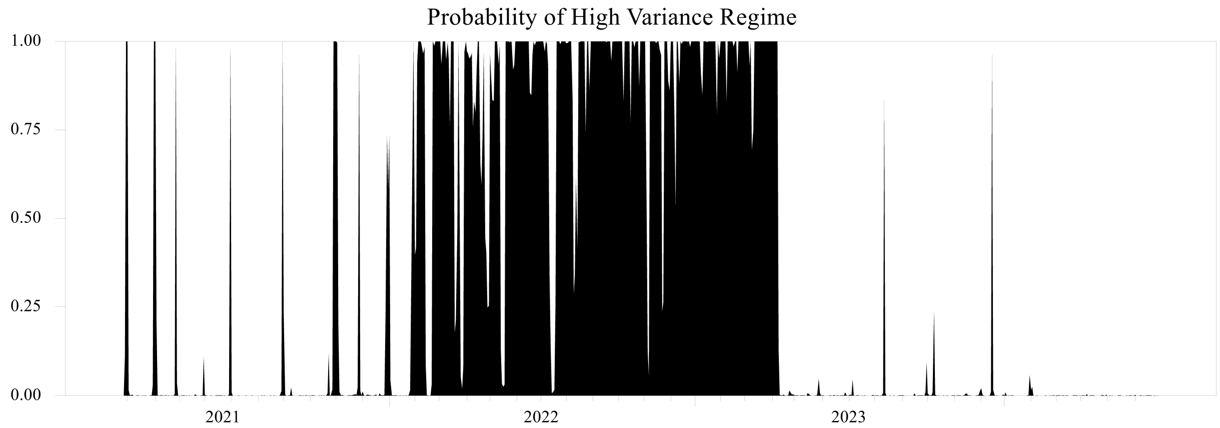


Figure C.5: Specification 8, TRI, BEIR 2Y.

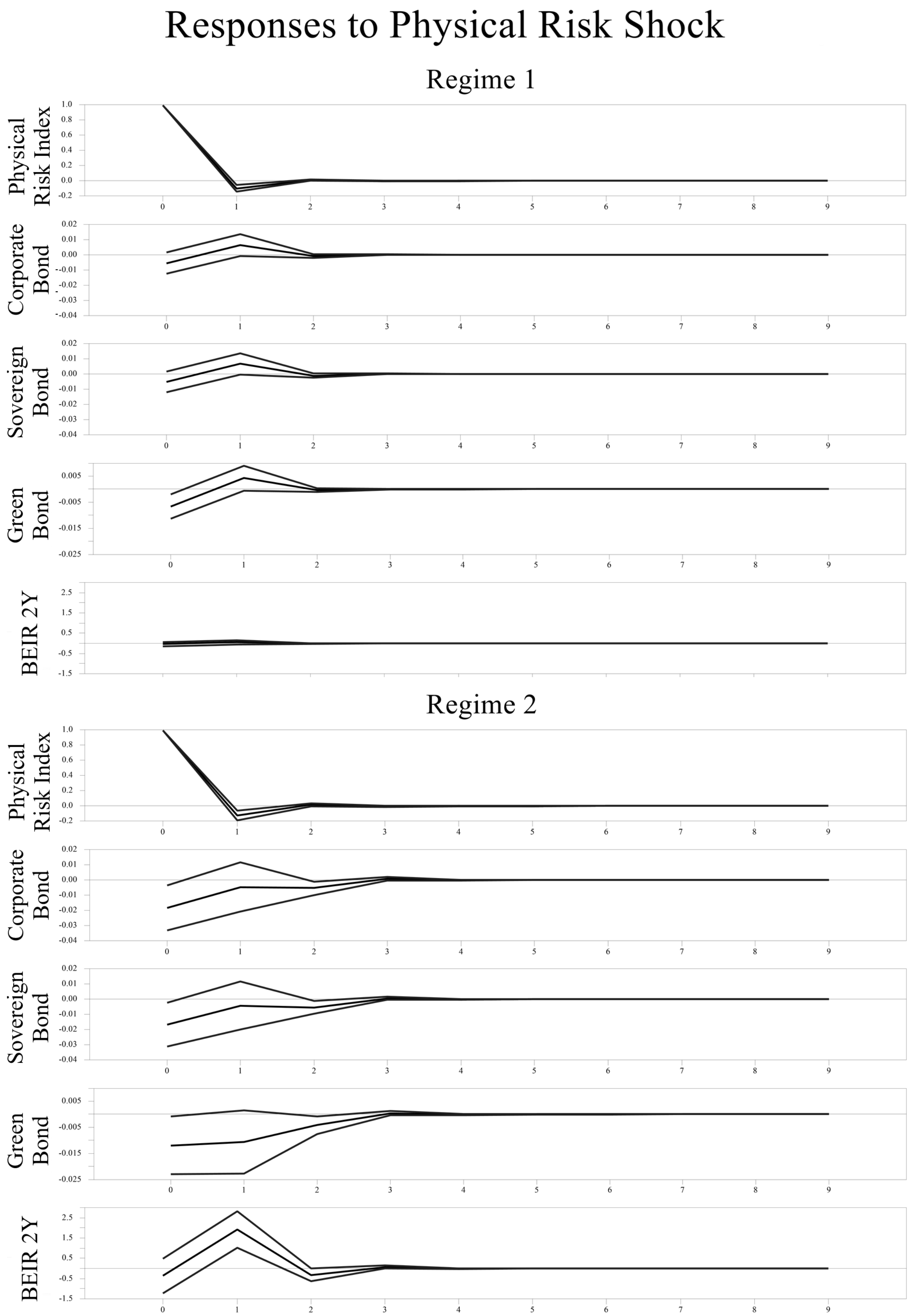


Figure C.6: Specification 5, PRI, BEIR 2Y. Responses to a climate-related risk shock.

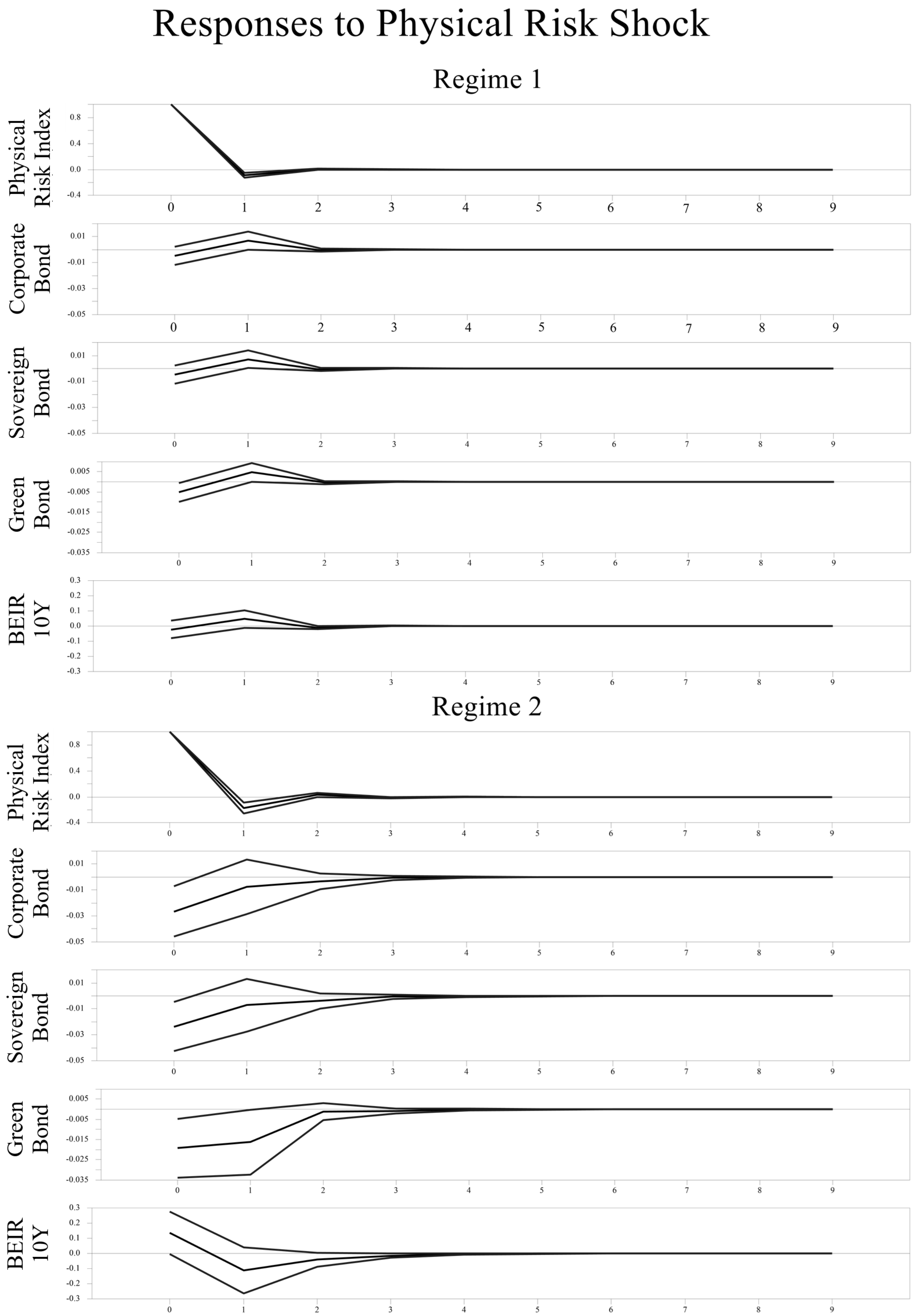


Figure C.7: Specification 6, PRI, BEIR 10Y. Responses to a climate-related risk shock.

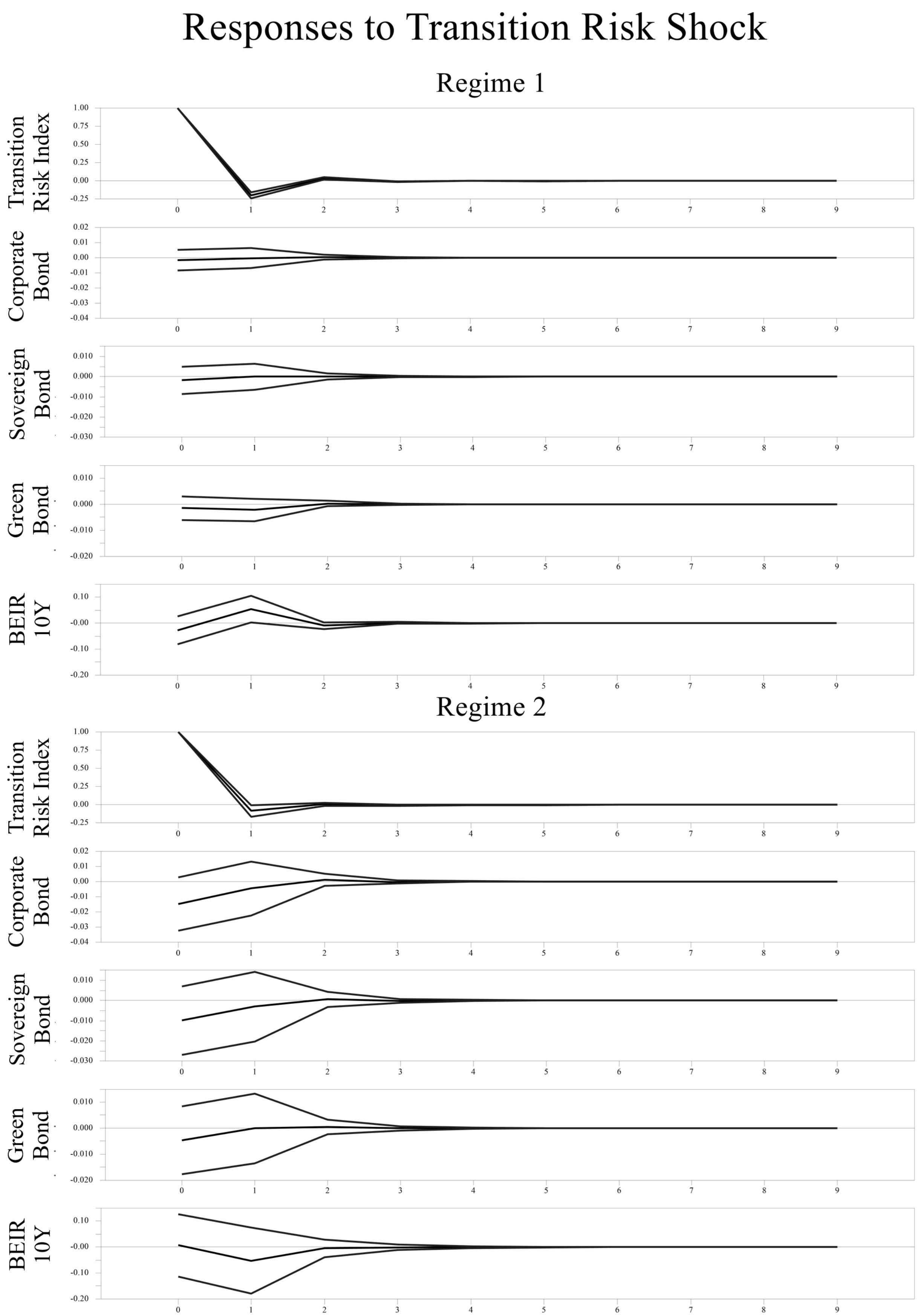


Figure C.8: Specification 7, TRI, BEIR 10Y. Responses to a climate-related risk shock.

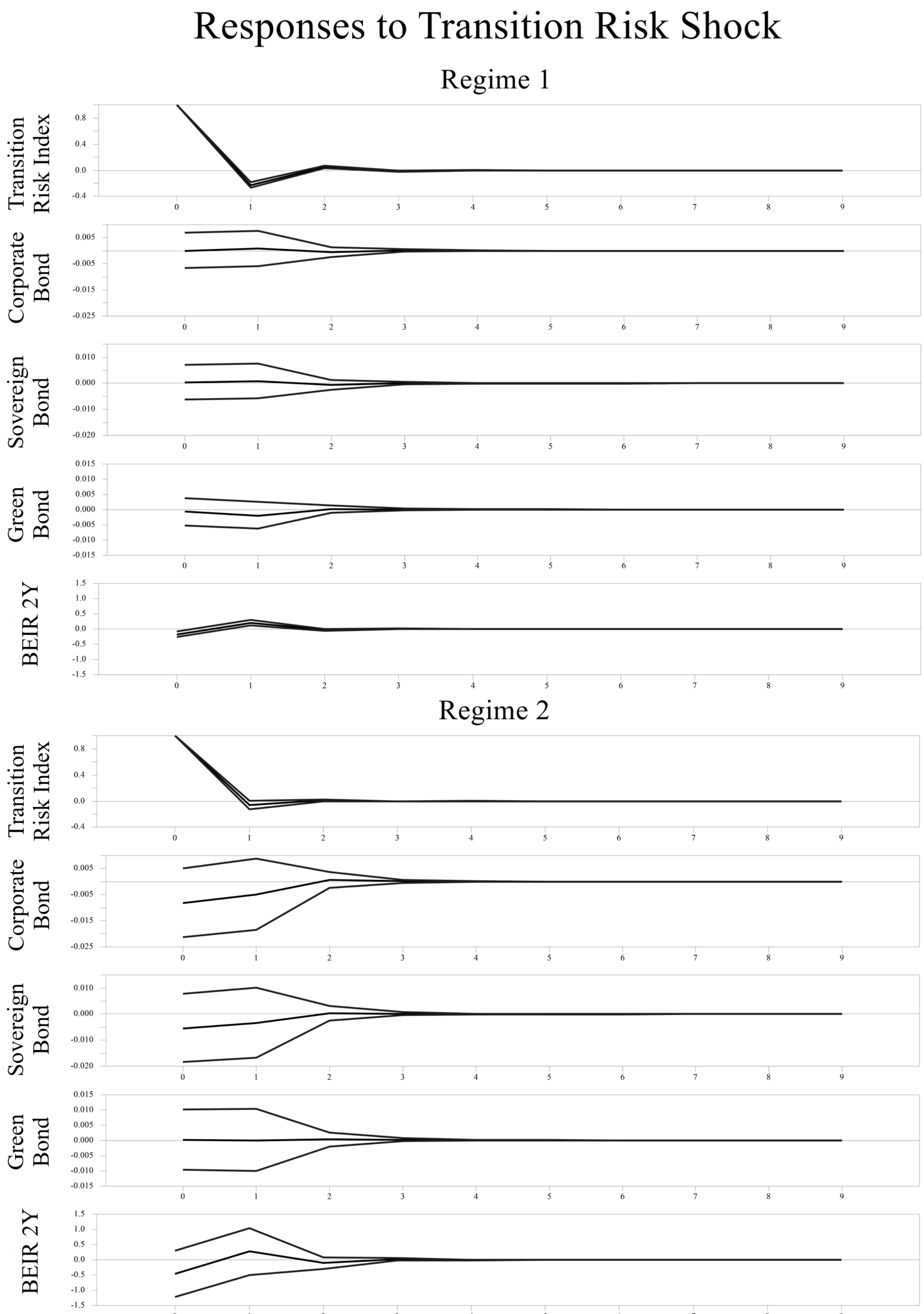


Figure C.9: Specification 8, TRI, BEIR 2Y. Responses to a climate-related risk shock.

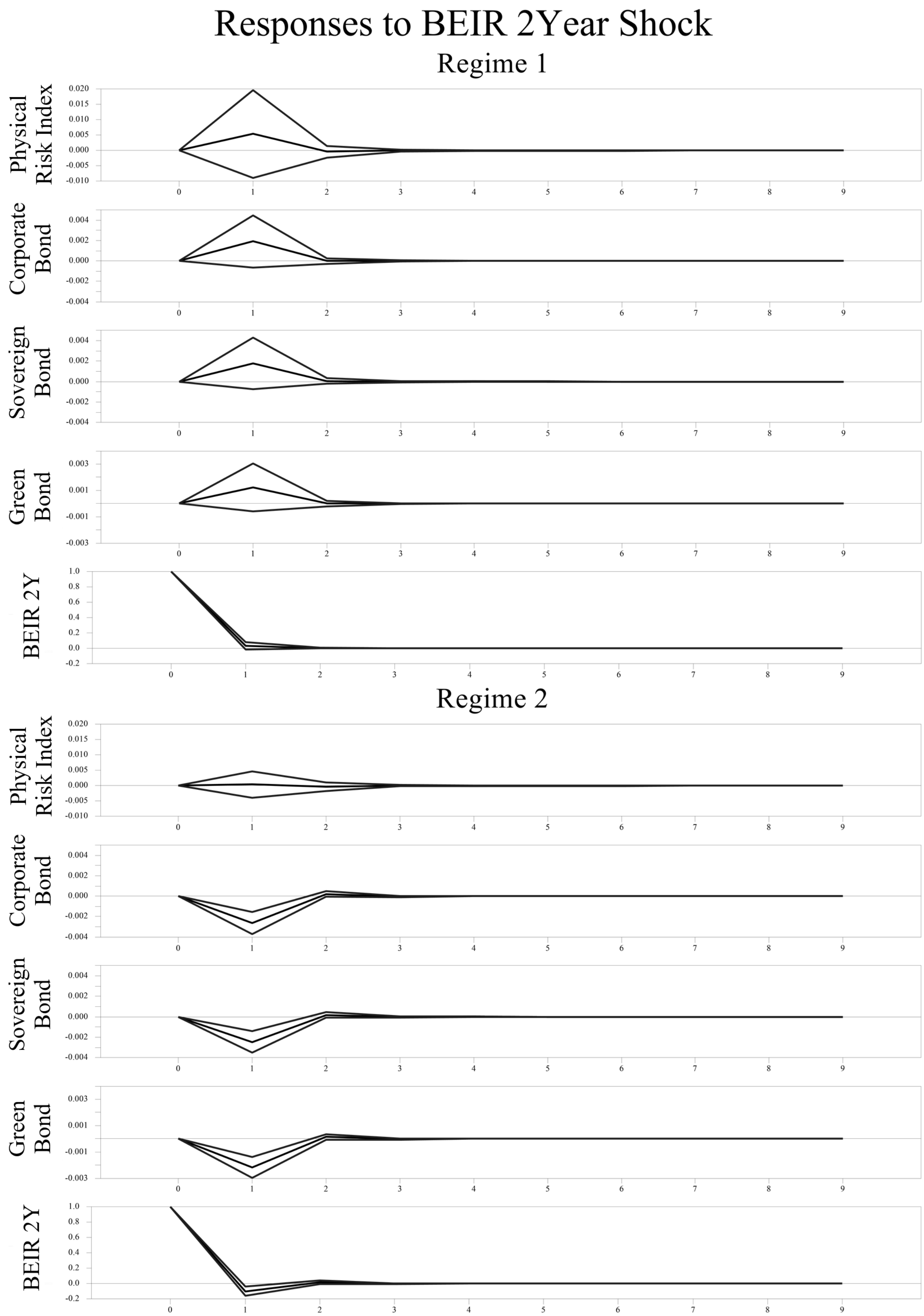


Figure C.10: Specification 5, PRI, BEIR 2Y. Responses to a breakeven-inflation shock.

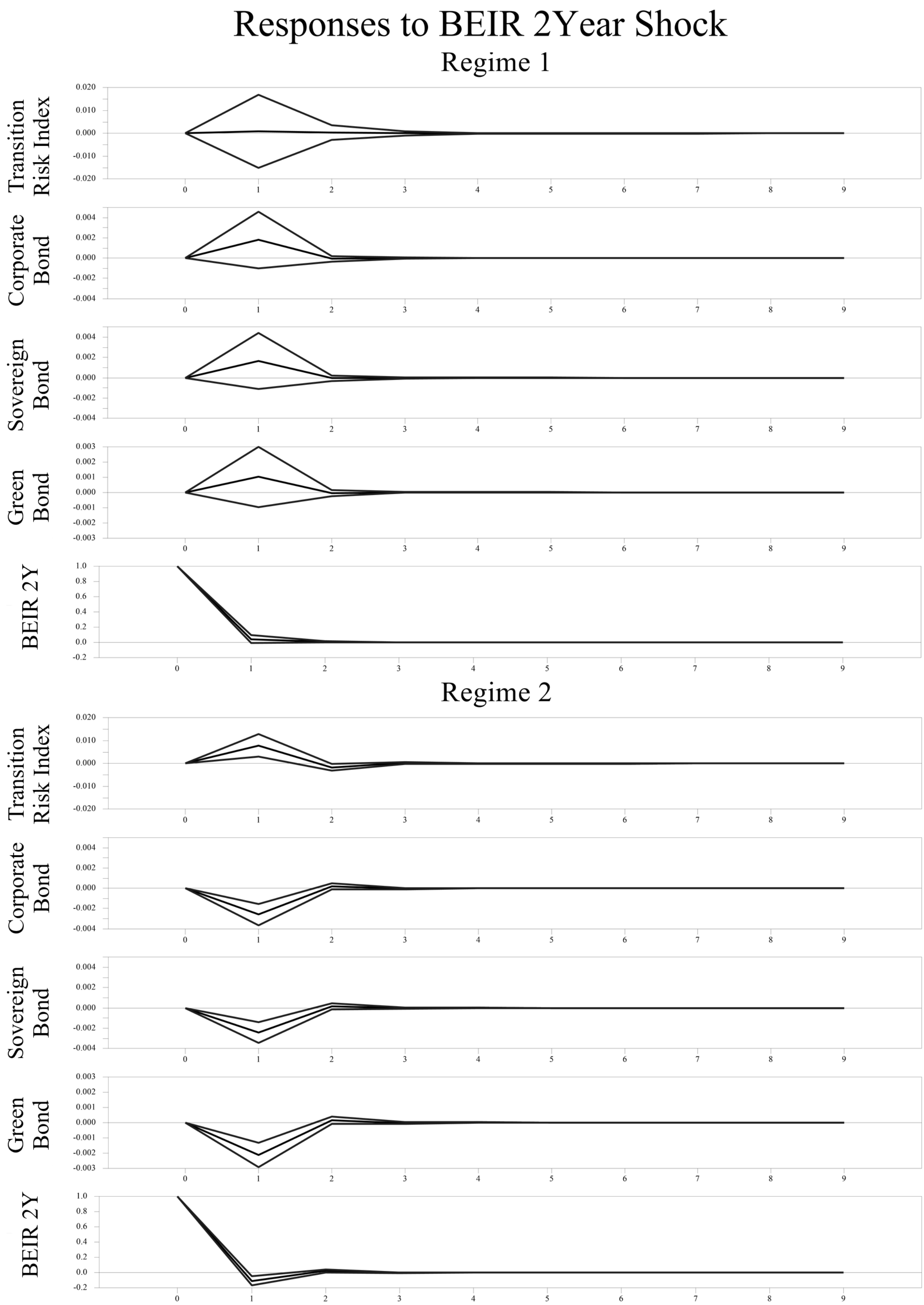


Figure C.11: Specification 8, TRI, BEIR 2Y. Responses to a breakeven-inflation shock.

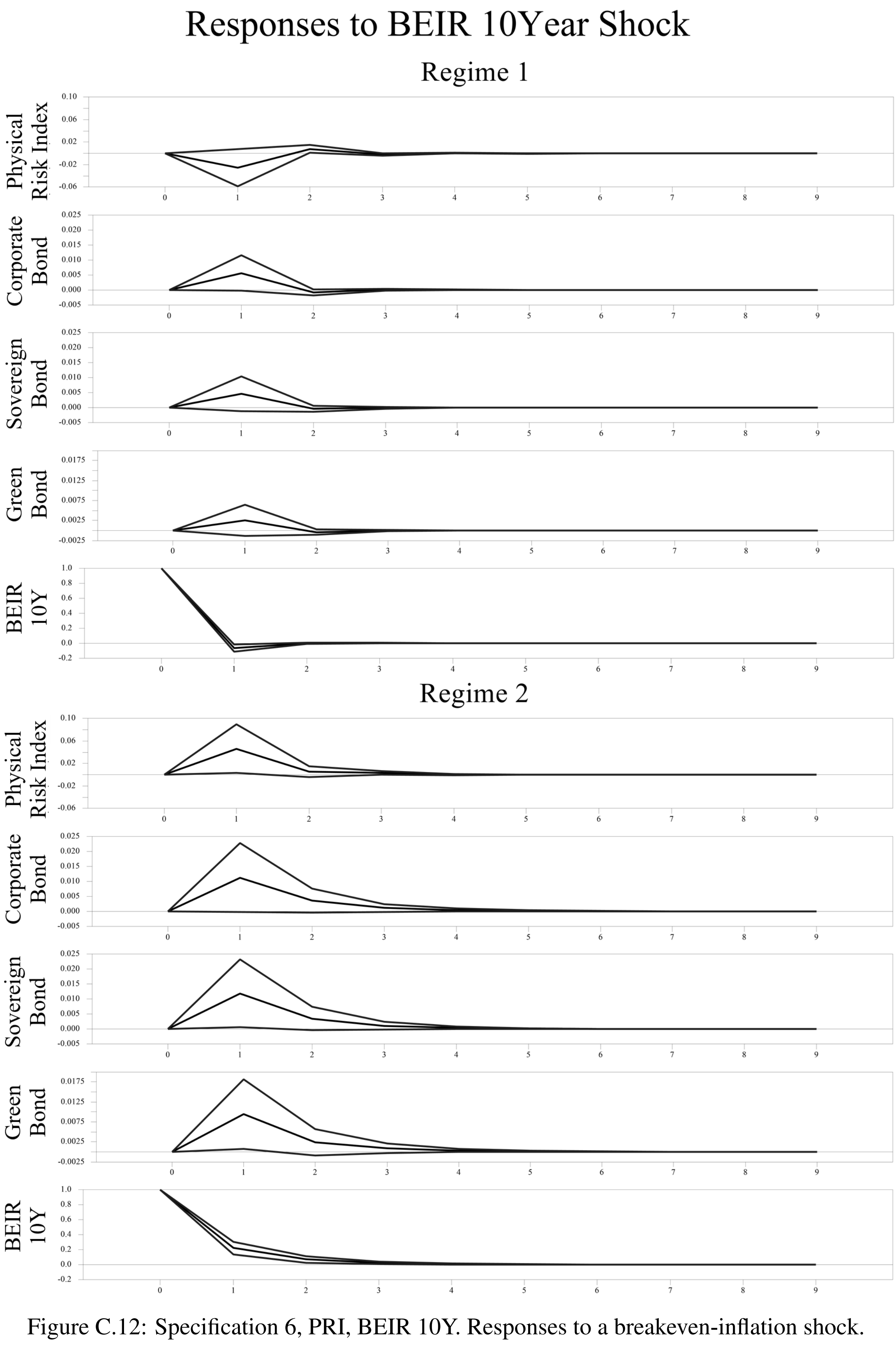


Figure C.12: Specification 6, PRI, BEIR 10Y. Responses to a breakeven-inflation shock.

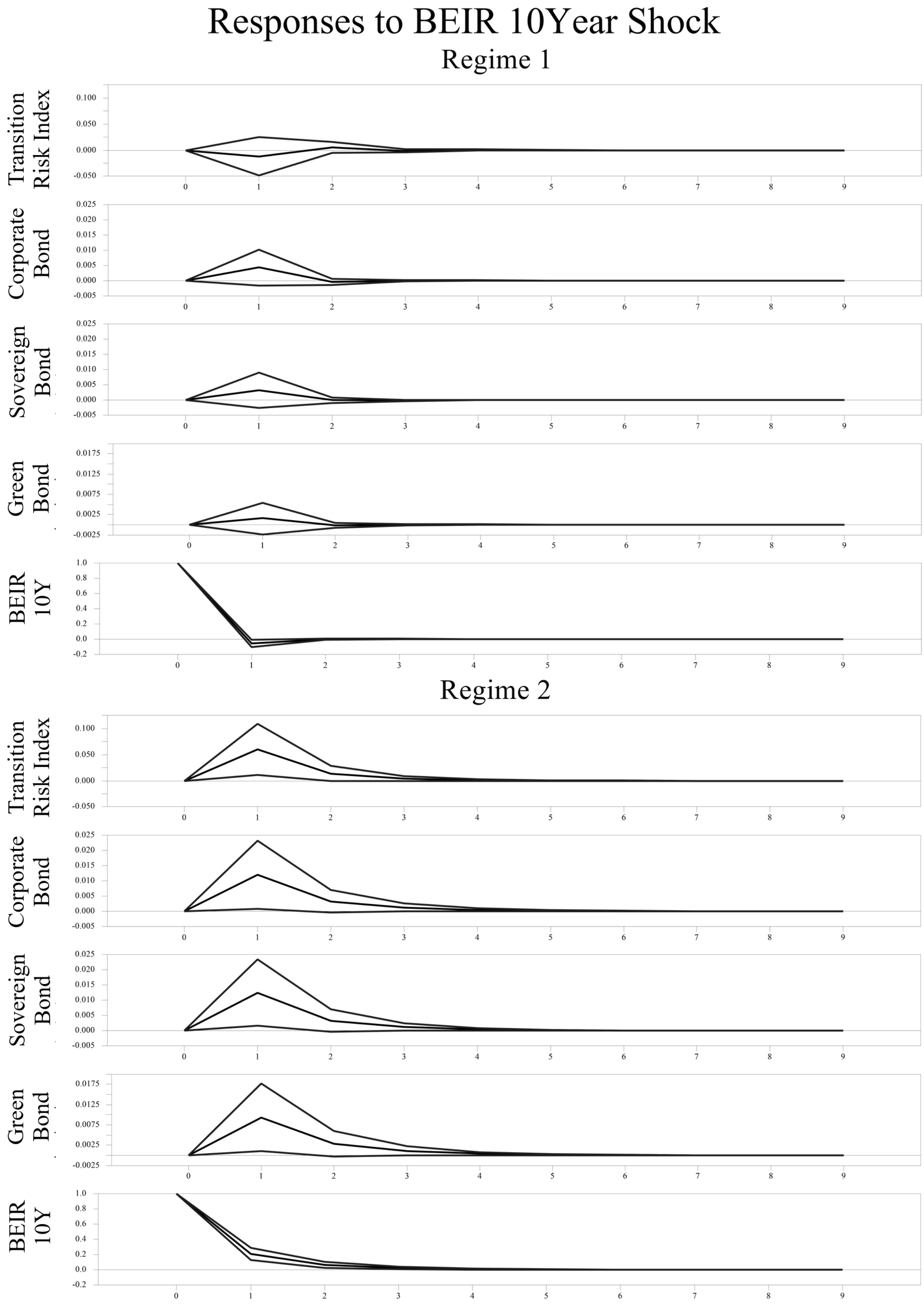


Figure C.13: Specification 7, TRI, BEIR 10Y. Responses to a breakeven-inflation shock.

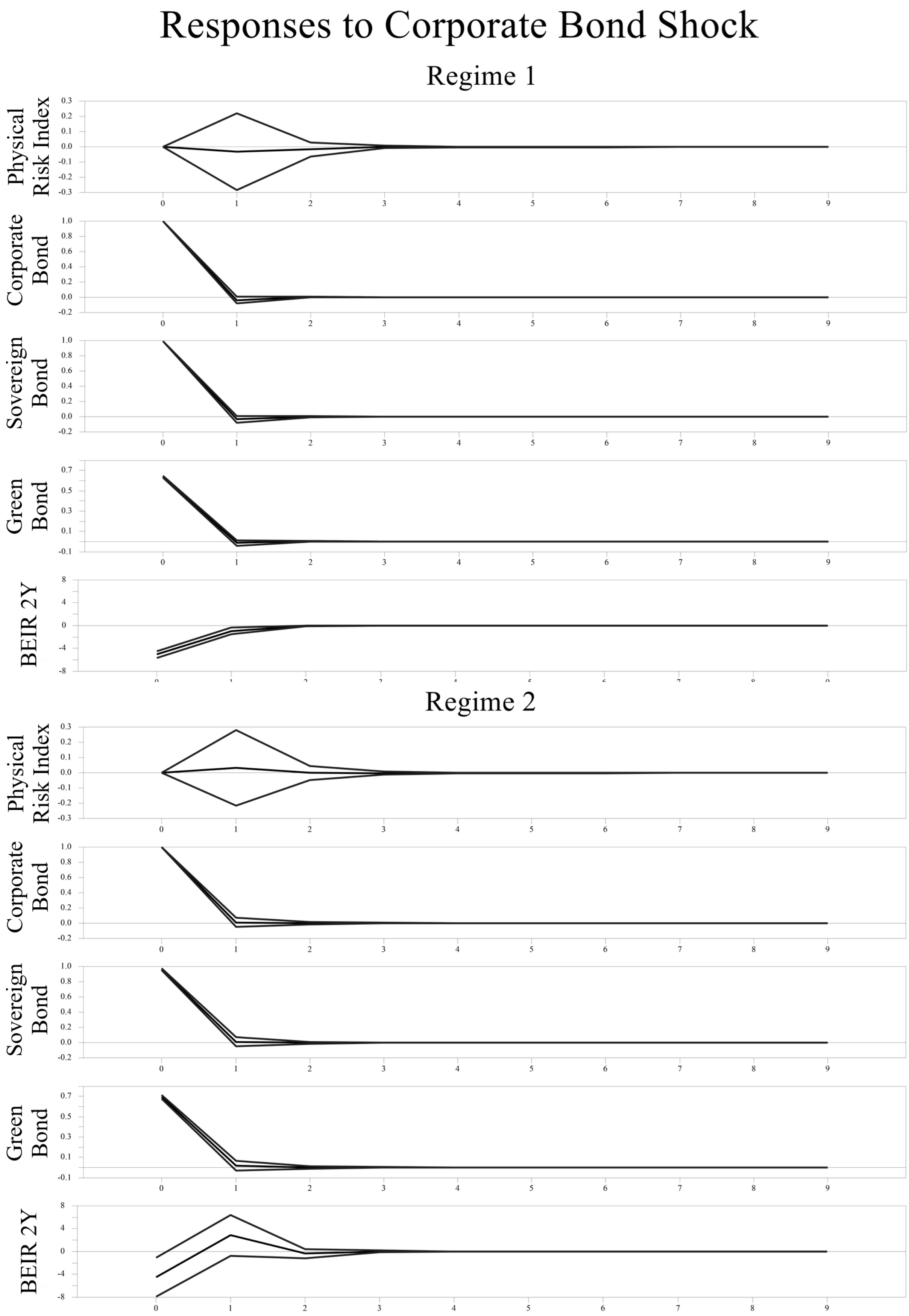


Figure C.14: Specification 5, PRI, BEIR 2Y. Responses to a corporate-bond shock.

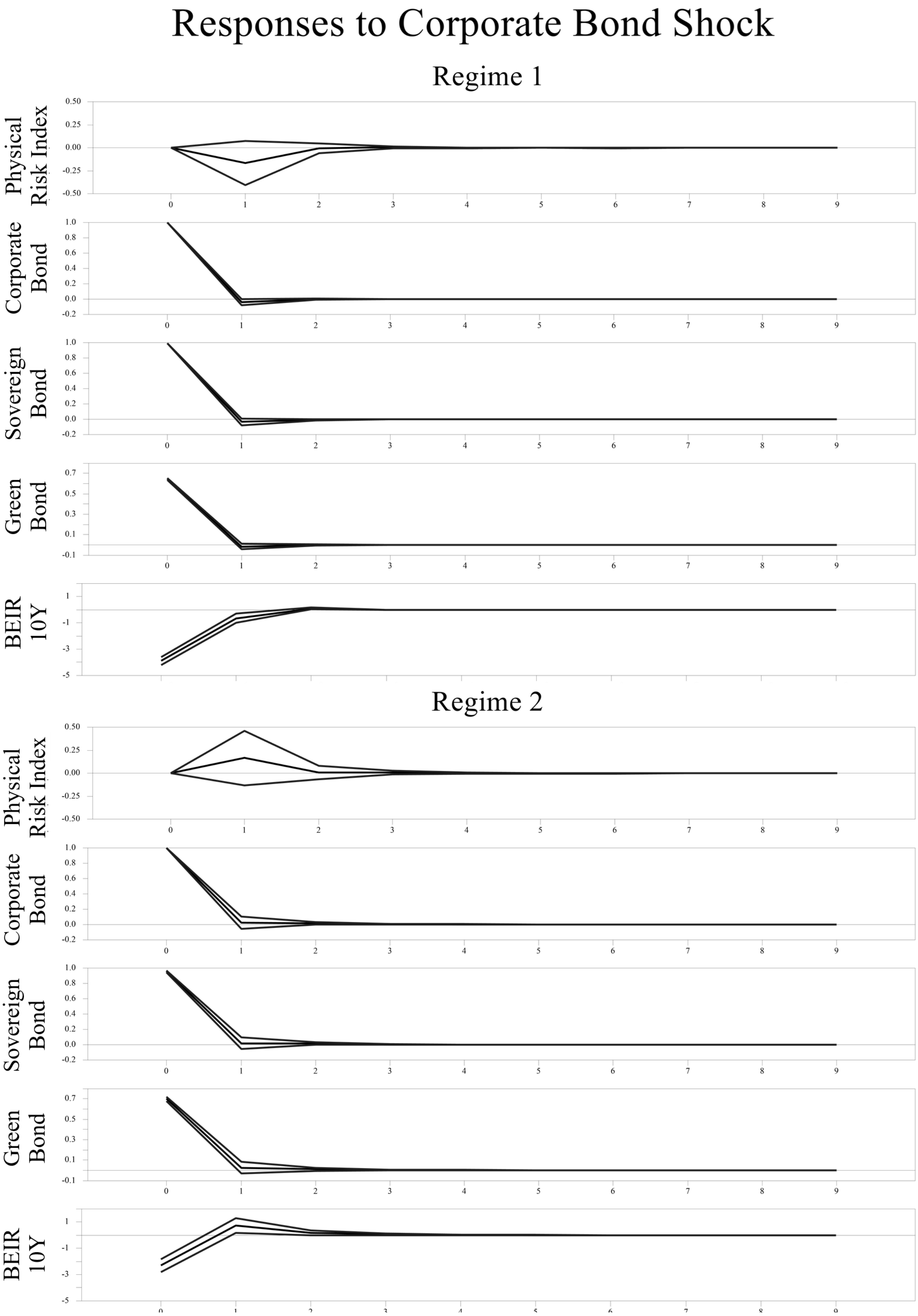


Figure C.15: Specification 6, PRI, BEIR 10Y. Responses to a corporate-bond shock.

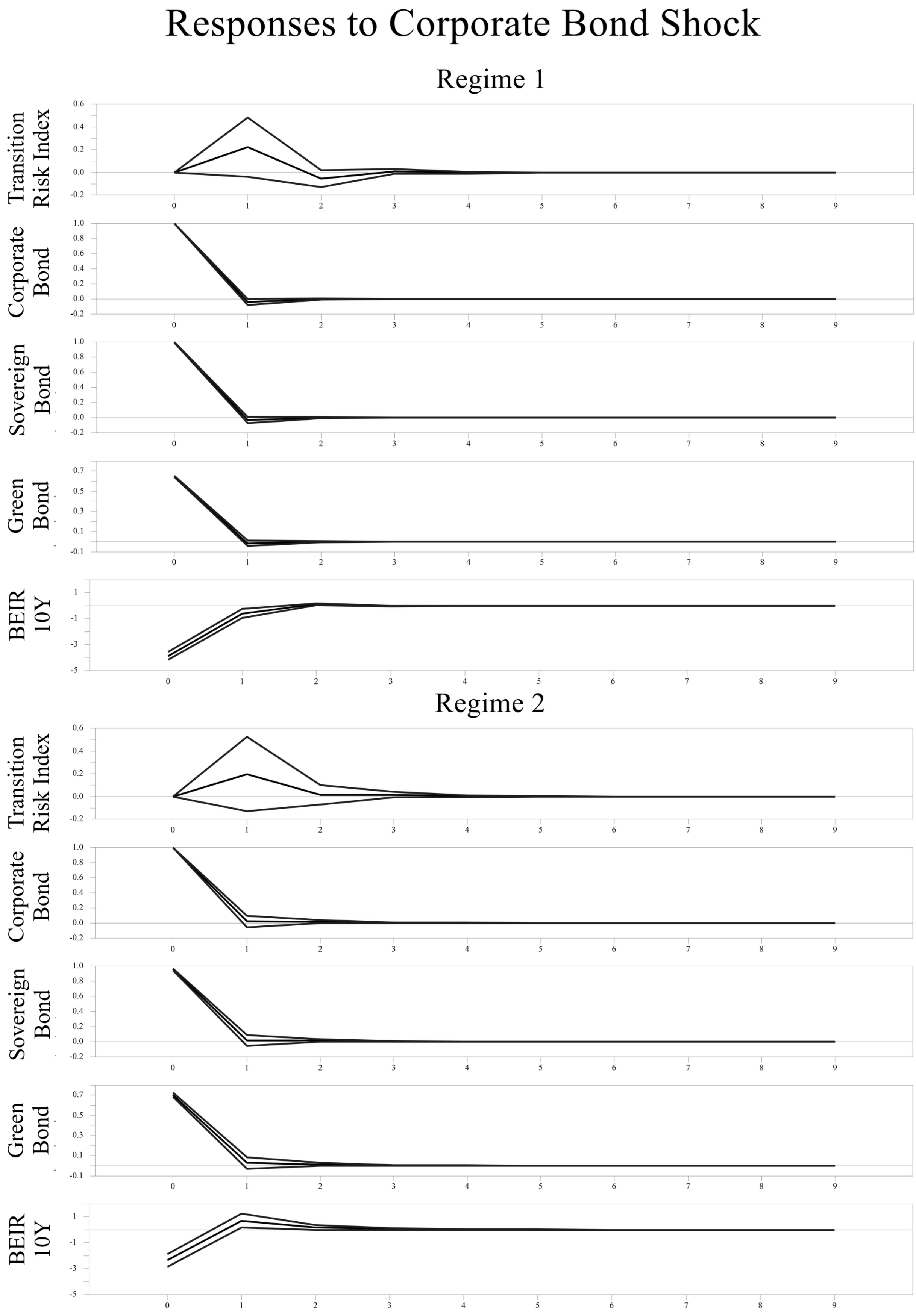


Figure C.16: Specification 7, TRI, BEIR 10Y. Responses to a corporate-bond shock.

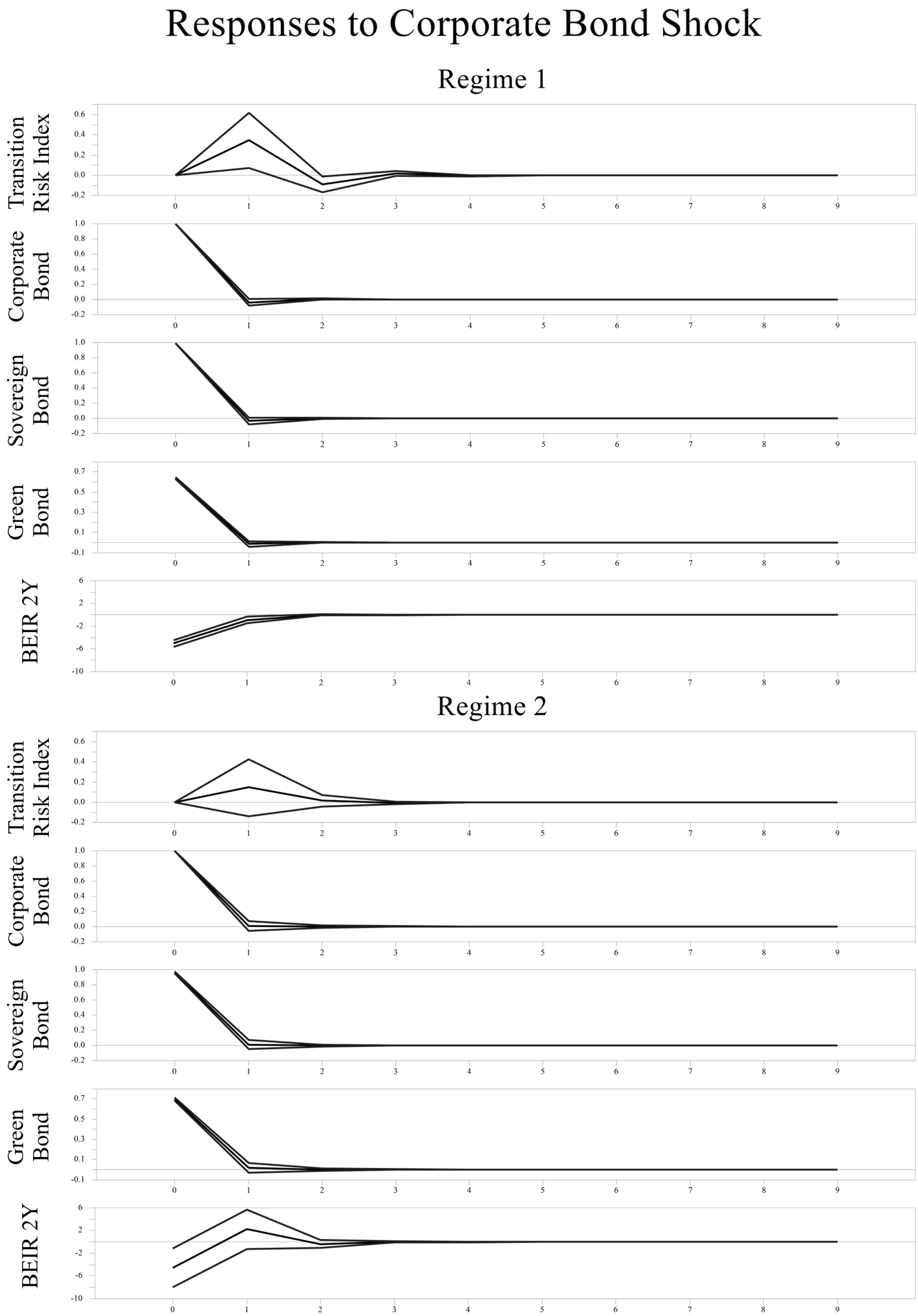


Figure C.17: Specification 8, TRI, BEIR 2Y. Responses to a corporate-bond shock.

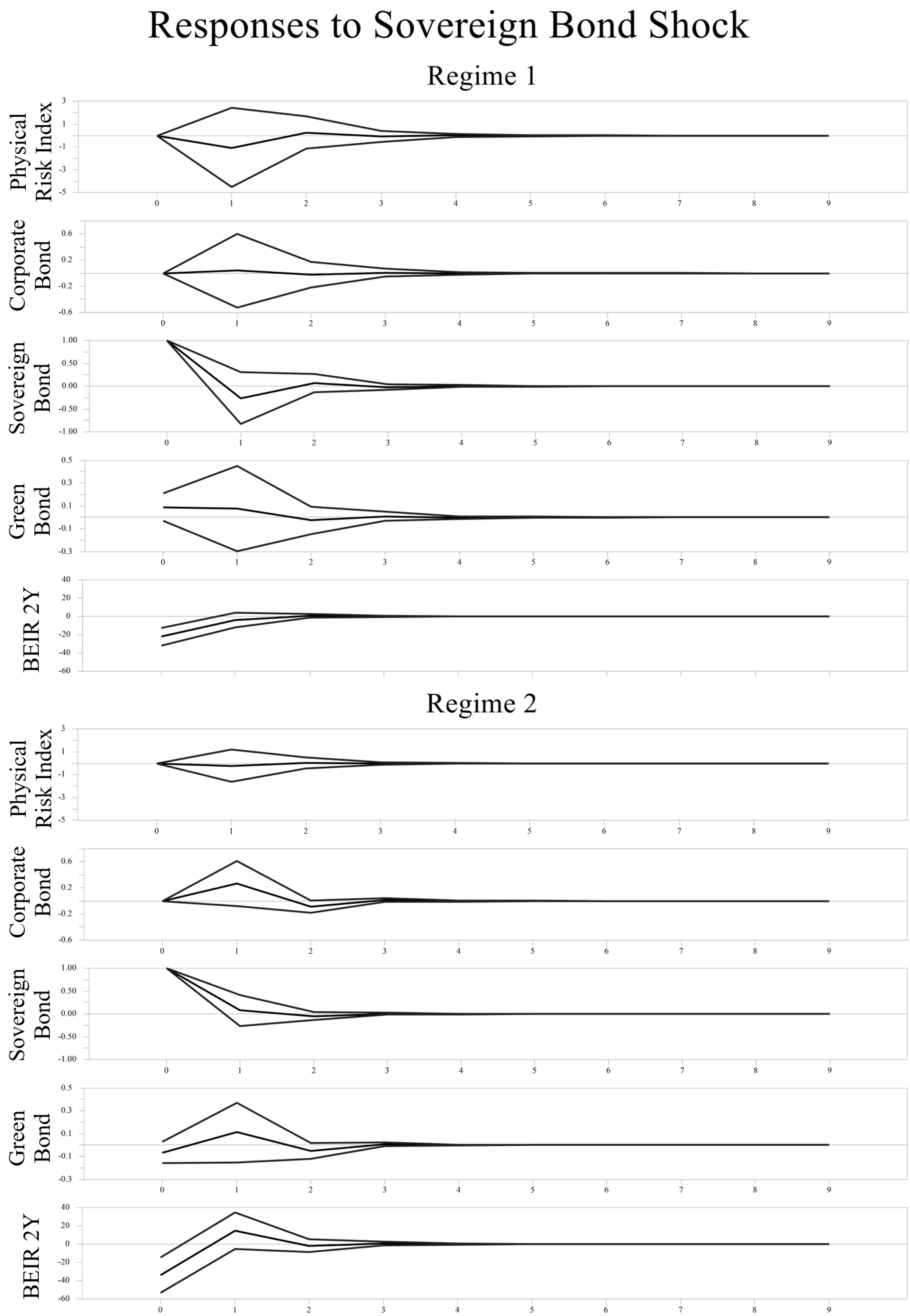


Figure C.18: Specification 5, PRI, BEIR 2Y. Responses to a sovereign-bond shock.

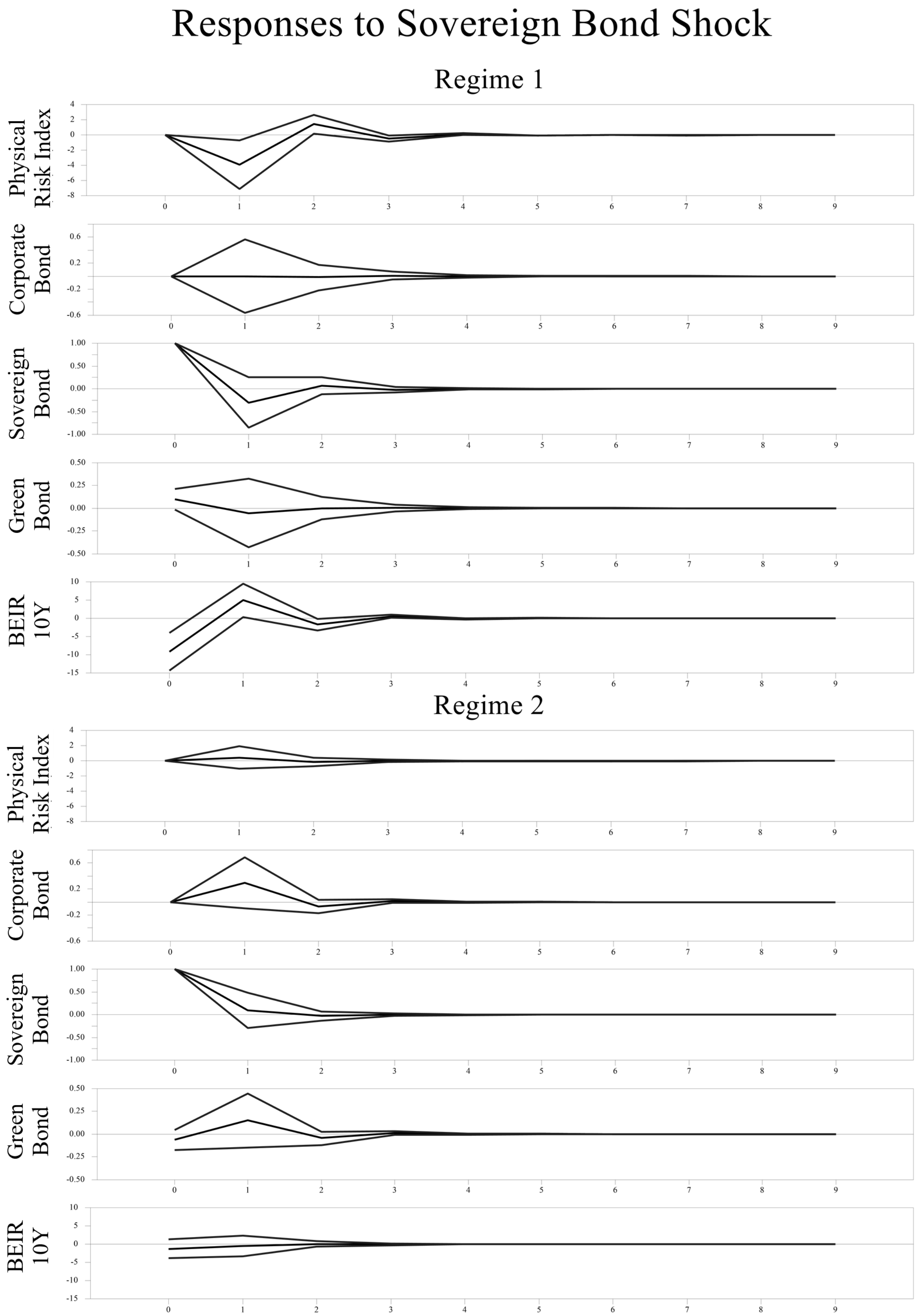


Figure C.19: Specification 6, PRI, BEIR 10Y. Responses to a sovereign-bond shock.

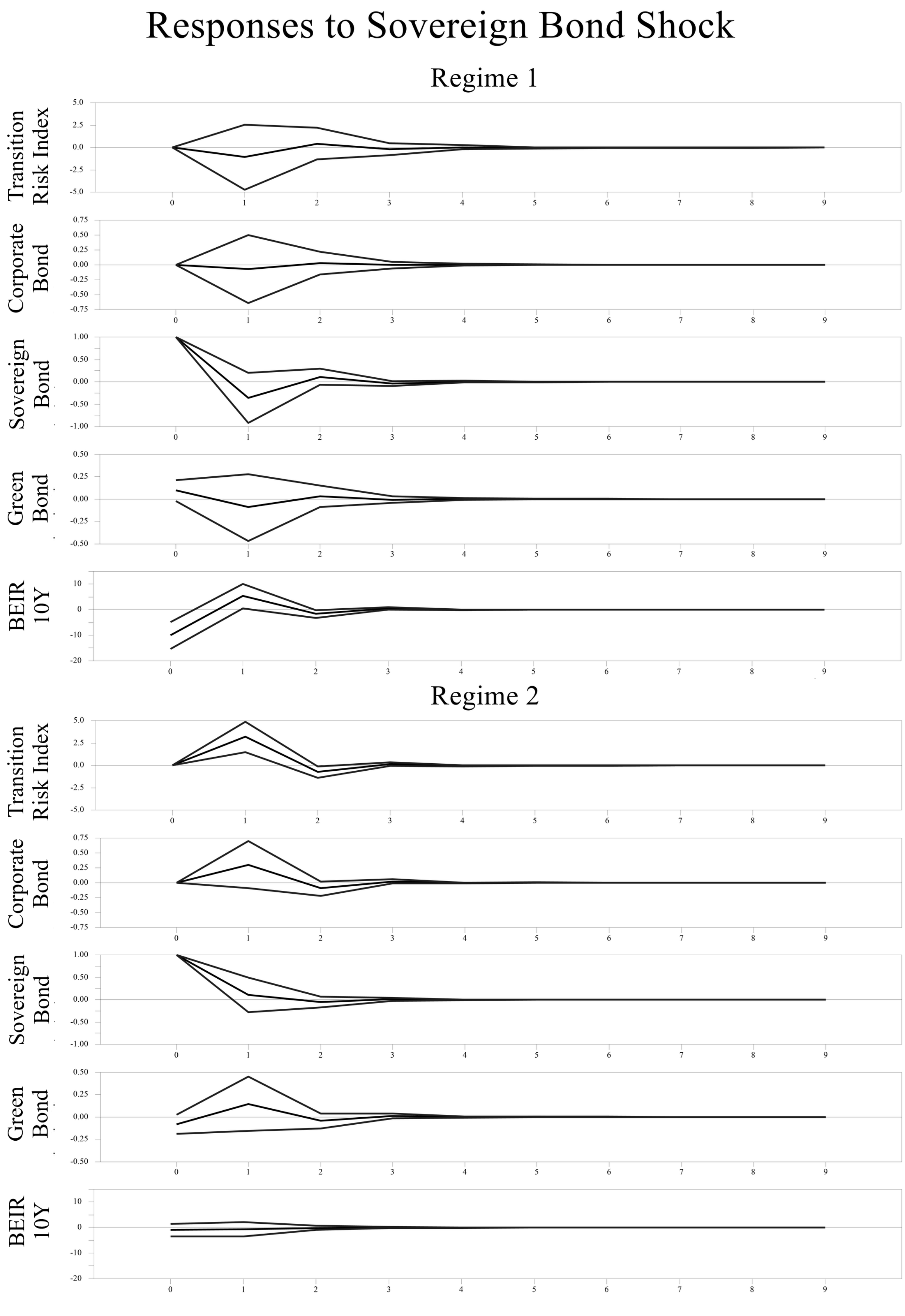


Figure C.20: Specification 7, TRI, BEIR 10Y. Responses to a sovereign-bond shock.

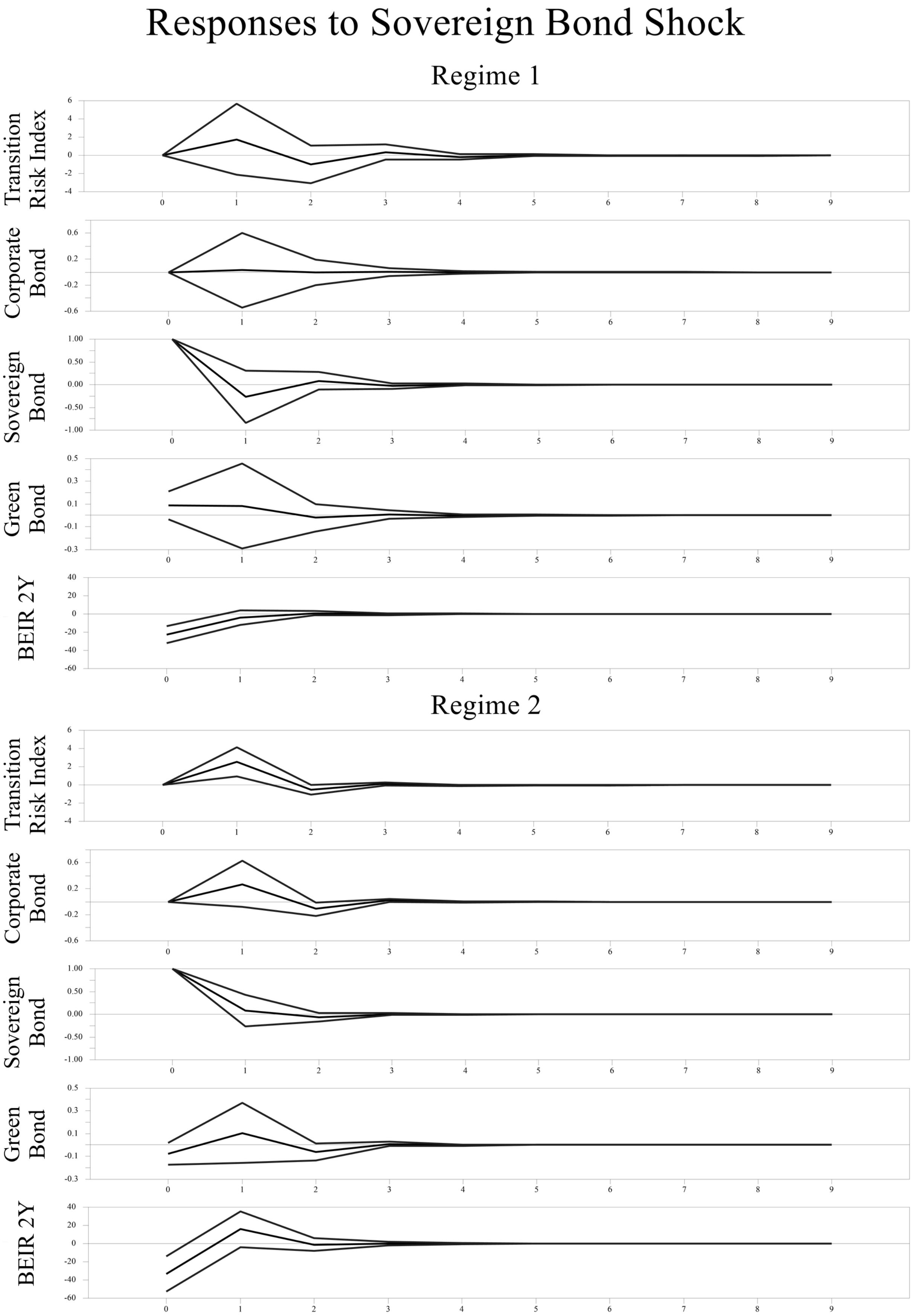


Figure C.21: Specification 8, TRI, BEIR 2Y. Responses to a sovereign-bond shock.

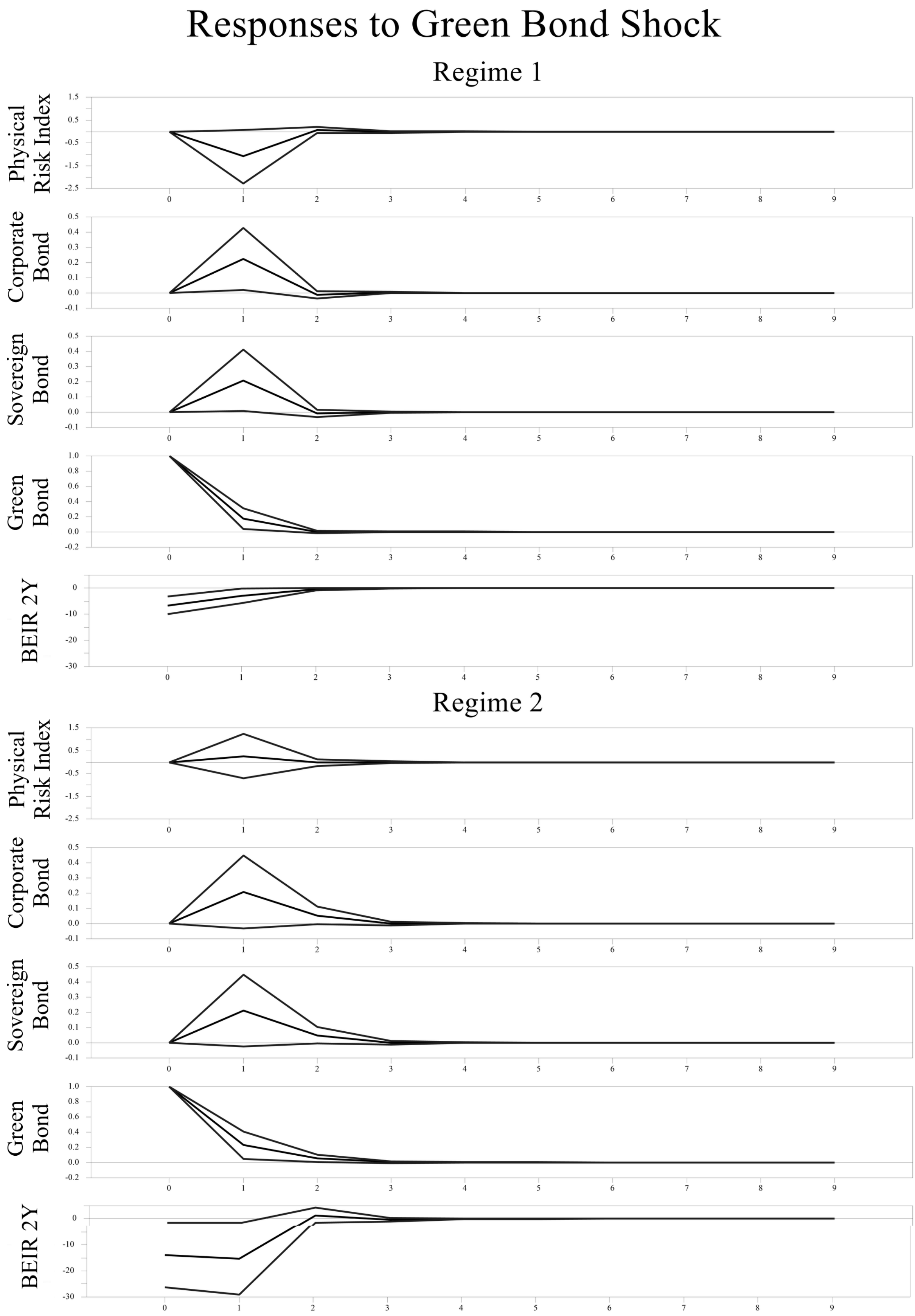


Figure C.22: Specification 5, PRI, BEIR 2Y. Responses to a green-bond shock.

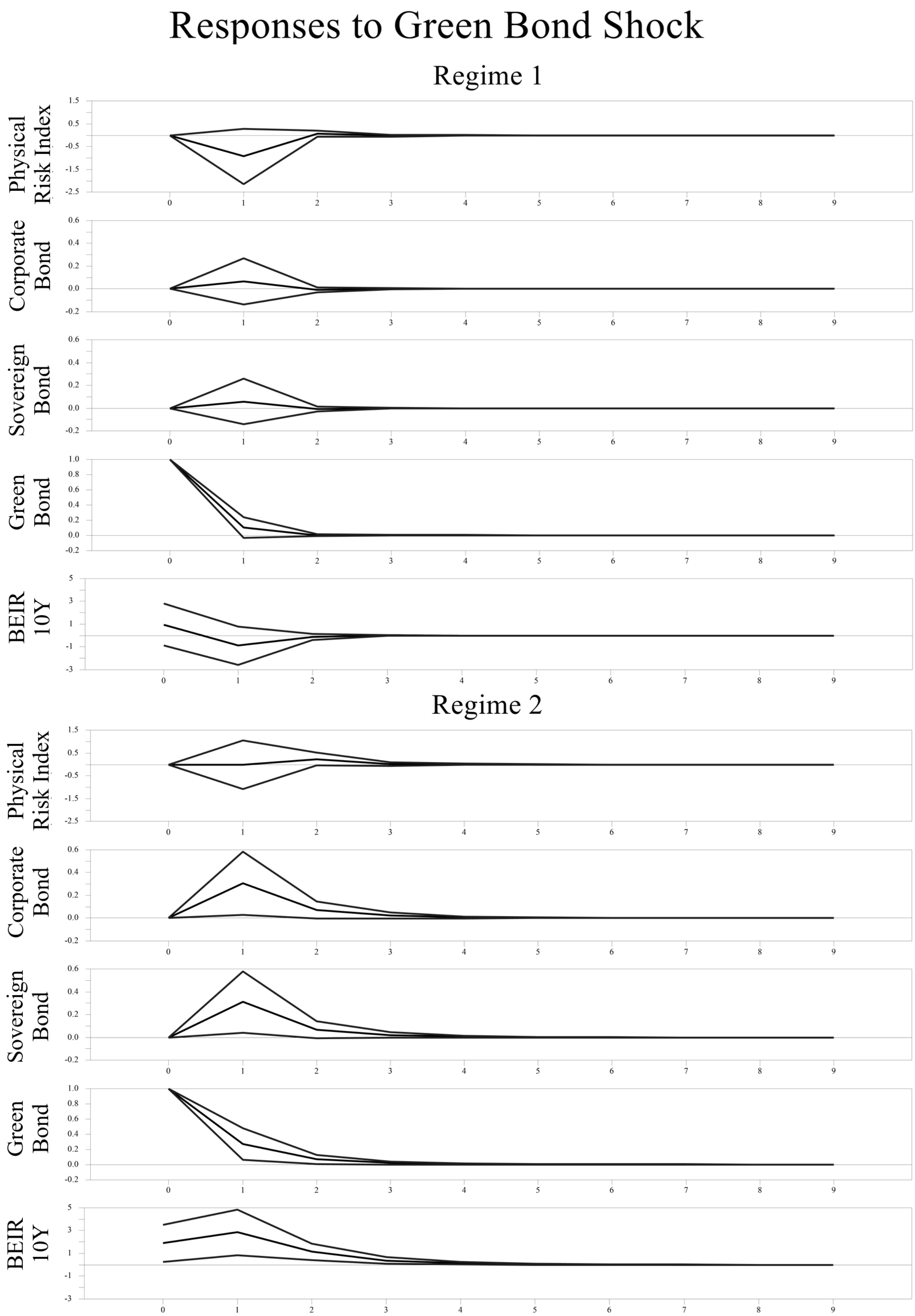


Figure C.23: Specification 6, PRI, BEIR 10Y. Responses to a green-bond shock.

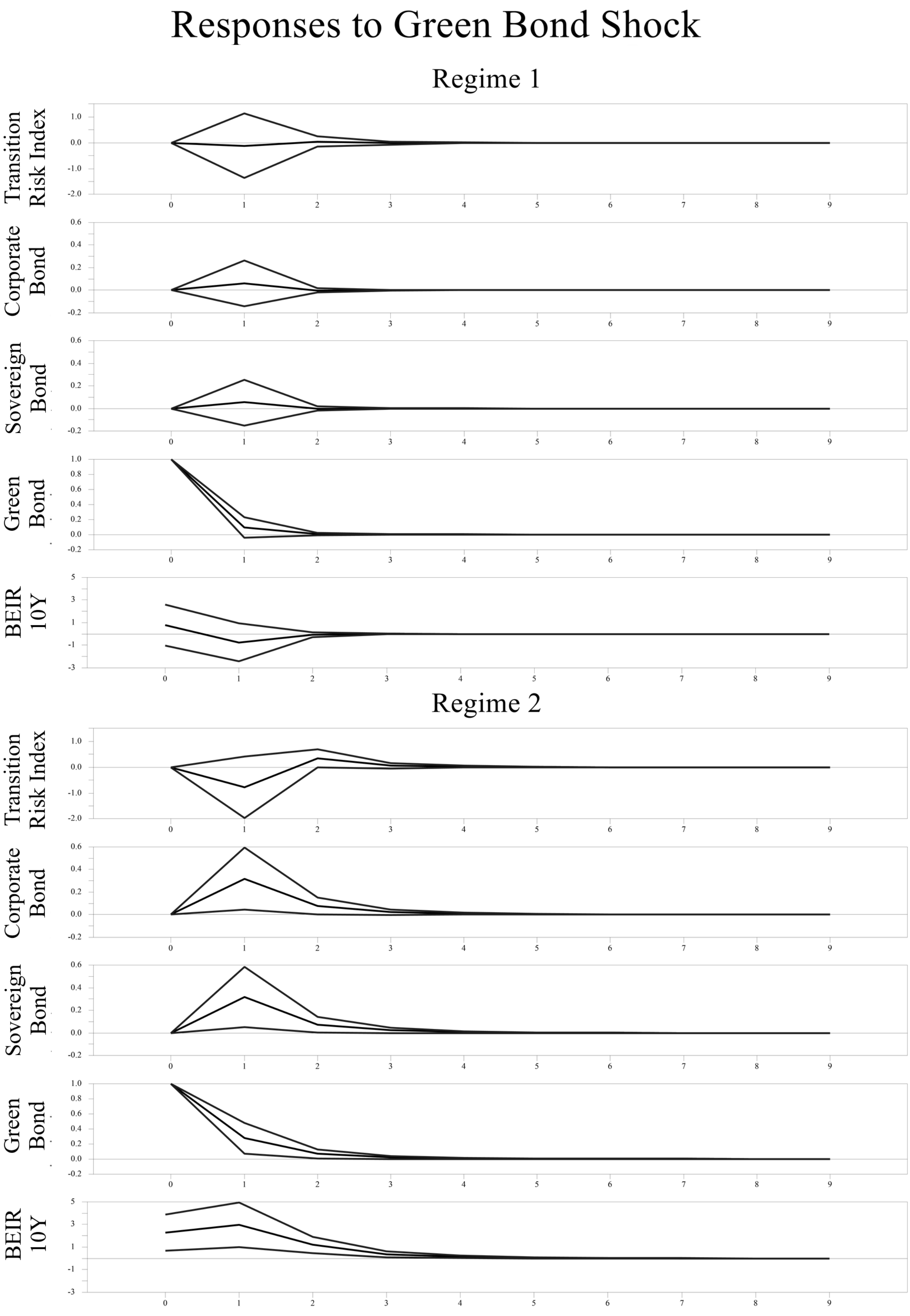


Figure C.24: Specification 7, TRI, BEIR 10Y. Responses to a green-bond shock.

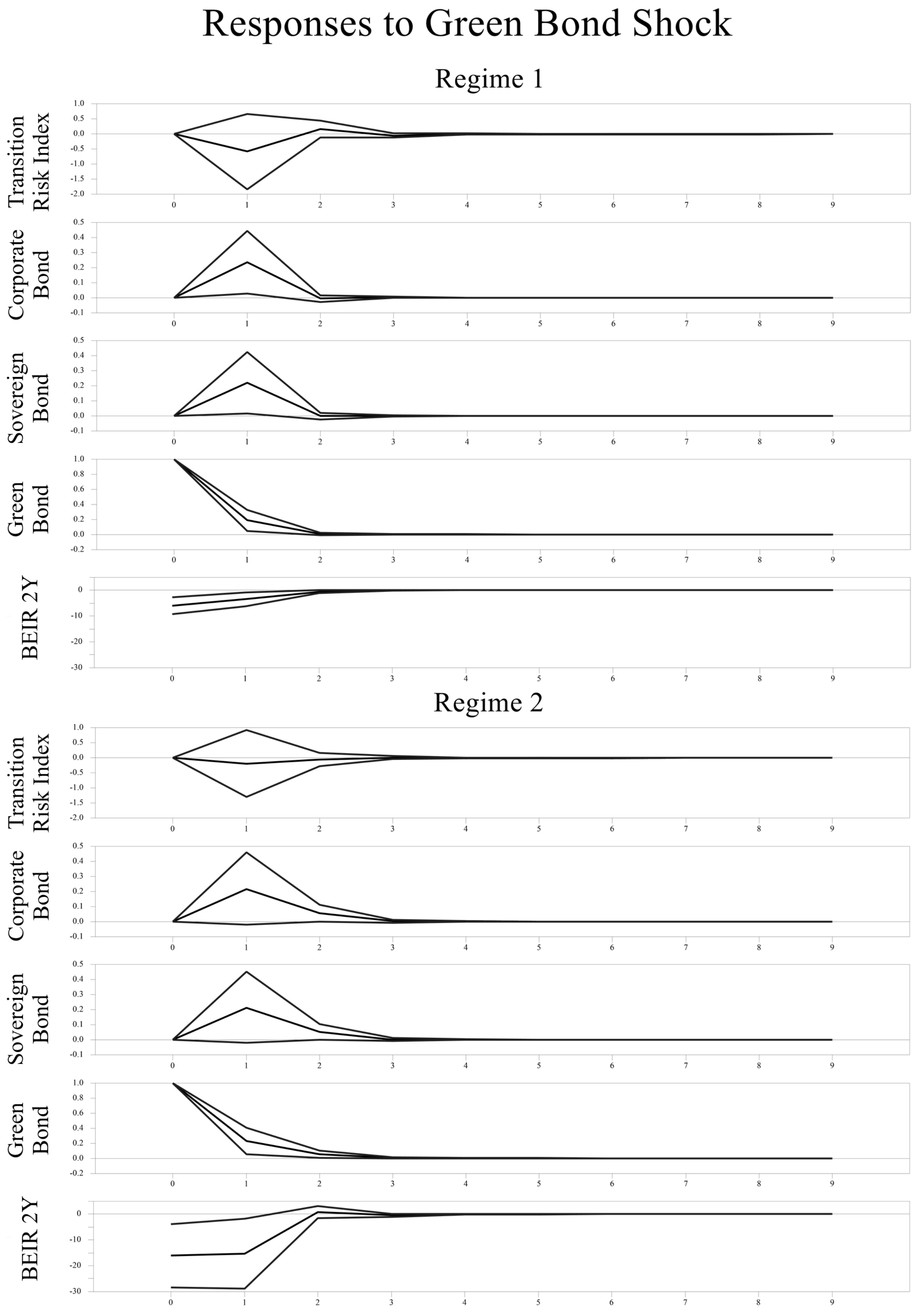


Figure C.25: Specification 8, TRI, BEIR 2Y. Responses to a green-bond shock.

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**Chapter 2**

# Concluding Chapter

# 1 Final chapter

As outlined in the introduction, this concluding chapter aims to enhance communication among and offer guidance to researchers and policymakers by highlighting the potentials of the applied methods for informing risk governance in economic policy. This builds on the broader context of current global issues established in the introductory chapter, which assumes that policymakers will be progressively confronted with shocks related to, for example, global warming or geopolitical tensions. These are intricate challenges where effective governance is linked to understanding and managing network effects. In this vein, in the main body of this thesis, Agent-based modeling (ABM), Input-Output Analysis (IOA), and Markov-Switching Vector Autoregression (MS–VAR) are applied. Methods representing three distinct approaches in the realm of complexity economics, supporting the governance of risks related to network effects from different angles. In this concluding chapter, these methods are reviewed structurally and epistemologically, and their strengths are related to a stylized policymaking process to highlight their potentials in supporting distinct steps within it.

## 1.1 Public Risk Governance

To begin, the ISO risk governance standard is outlined and delimited to establish a foundation for the subsequent analysis. Policies aimed at safeguarding the resilience and stability of economic and financial networks can be understood as risk governance. There are multiple step-by-step guidelines for risk governance. Murray and Enang (2022) discuss the use of guidelines originated in the private sector for the adoption by public institutions. They conclude that they are very similar and the best choice depends on the context. Thus, I chose the risk governance process according to the ISO 31000:2018 standard for risk management as a frame-

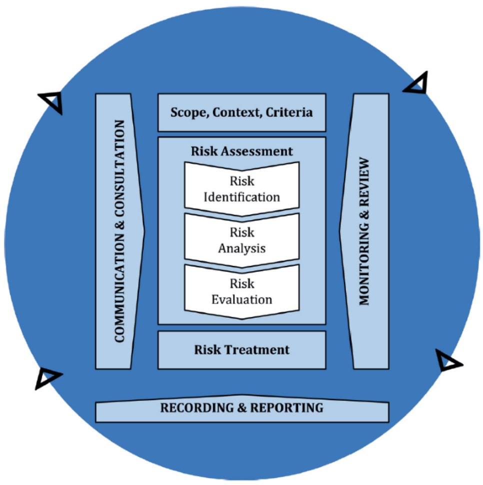


Figure 1: Overview of the risk management process. Source: ISO 31000 (ISO, 2018)(p.9)

work for my discussion, which offers a generic and widely adopted framework, not only by the private sector (being termed the gold standard (Dali and Lajtha, 2012)) but also a prominent choice by central banks (Central Banking, 2024).

In order to understand the process as outlined in the ISO 31000 standard, it is important to emphasize that, although the process is depicted as sequential, it should not be interpreted as iterative in practice, but rather nonlinear. In this discussion, I will focus on the central elements of the process, as depicted in Figure 1. While the surrounding elements, such as communication and consultation, as well as recording and reporting, are essential to the process, these elements have procedural rather than analytical functions. Hence, I consider elaborations on these steps redundant. In addition, the step "Risk Assessment" comprises three sub-steps. Among these, "Risk Evaluation" is not discussed in detail, as it only involves comparing the analyzed risks with predefined criteria, both of which are established in earlier steps. By contrast, the remaining sub-steps are treated as distinct components. Thus, the discussion focuses on (1) "Scope, Context, and Criteria", (2) "Risk Identification", (3) "Risk Analysis", and (4) "Risk Treatment".

*Step 1: "Scope, Context, and Criteria"* sets the foundation for risk management by defining the strategic goals that are to be safeguarded and following on the scope in which risks are considered, by specifying spatial and temporal boundaries of risk assessment (what will be investigated?), and formulating risk criteria. Risk criteria clarify how different levels of risk should be handled. Lower-level risks may be deemed negligible, while higher levels may require changes in assessment techniques, adjustments to what is being assessed, or specific mitigation measures.

*Step 2: "Risk Identification"* involves discovering, acknowledging, and describing potential threats and vulnerabilities that could hinder achieving the organizational objectives.

*Step 3: "Risk Analysis"* is the analytical core of the process and aims to understand the risk. In particular, the causes and mechanisms of a risk event, the probabilities of occurrence, the probabilities and the severity of consequences, and existing controls and their effectiveness.

*Step 4: "Risk Treatment"* involves selecting, designing, and implementing appropriate responses to risk exposure. Strategies may include avoiding, reducing, sharing, or retaining the risk, depending on its acceptability and relevance to organizational goals. Furthermore, while monitoring is formally defined as a distinct step, the choice to expand or intensify the observation of a specific issue is also inherently part of this phase (ISO, 2018; IEC/ISO, 2019).

# 2 Review of models

Subsequently, the methods used in the previously presented projects will be reviewed and related to the selected steps of the ISO 31000 risk governance process. The discussion proceeds in a systematic and structured manner, examining each approach, ABM, IOA, and VAR, in turn. Within each project, specific instantiations from the broader methodological families are applied. Subsequently, I adopt deliberately broad, though not exhaustive, scopes of the method families. Each subsection begins with a concise overview of the broader methodological landscape, delineating the boundaries of the review[1]. To ensure this chapter is self-explanatory, I briefly review the approaches to provide a basis for the subsequent elaborations. These reviews encompass the structural components of models, including the selection of variables, the design of relationships between them, and the underlying principles that link the model structures to reality. Thereby, the epistemological background is established to relate the methods' strengths to their contributions to specific steps in the risk governance process.

## 2.1 Vector Autoregressions

At the outset, let us examine the landscape that frames VAR modeling and set the scope of the subsequent review. VAR models represent a cornerstone of modern multivariate time series analysis, introduced by Sims (1980). VAR models have found widespread application in both economics and finance, and many extensions have been developed for different purposes. The traditional applications are in the field of macroeconomics on the aggregate dynamics, fore-

[1] Notwithstanding the growing relevance of machine learning and artificial intelligence extensions, their exploration is beyond the scope of this study.

casting key variables like GDP growth, inflation, and unemployment, and conducting policy analysis (Sims, 1980; Stock and Watson, 2001). However, given the focus of this work on risk governance, this review is primarily concerned with model variations that provide the ability to account for complexity and to study specific transmission channels within networks. Various approaches in economics build on the understanding of the economy as a network. Among those are Large VARs, Global VARs, and Network VARs. Large VARs follow the basic VAR form, only including a high number of variables.[2] Yet, this expansion leads to quadratic parameter growth that can exceed observations (risk of overfitting and spurious inference). This challenge that can be mitigated by leveraging structural knowledge of the target system and implementing appropriate modifications as done in Global and Network VARs (Chudik and Pesaran, 2016; Ahelegbey et al., 2021). In finance risk governance tends to dominate and VARs are extensively used for modelling how assets jointly interact and this allows for an assessment of market linkages and for quantifying the extent of risk transmission (Tsay, 2005; Zopounidis et al., 2021).

To illustrate the estimated dynamical interlinkages among variables, Impulse Response Functions (IRFs) are used. When residuals exhibit contemporaneous correlation, one may either depict the system's expected contemporaneous comovement to a shock through Generalized IRFs or isolate contemporaneous "causal" effects via Orthogonalized IRFs. Both will subsequently be accounted for, as well as causal inference approaches such as Granger causality. Although this method is not confined to VAR models, testing for predictive influence is particularly insightful (Chamberlain, 1982).

Further considered will be innovations to address time-varying structures and nonlinearity, acknowledging that economic relationships are often not static. With regard to risk governance, VAR variations capturing relationships in different regimes, e.g., in extreme phases, are particularly interesting.[3] Models enabling abrupt transitions between distinct regimes are Threshold or Markov-Switching VARs (Hamilton, 1989; Krolzig, 1997). Before exploring how VAR models

[2]Network VAR approaches with dynamically changing links, while promising such as Mantziou et al. (2024), are not included in this work.

[3]Accordingly, other approaches dealing with nonlinearities in time series, such as Time-Varying Parameter VARs (Hubrich and Tetlow, 2013) and Vector Error Correction Models (VECMs) for cointegrated variables (Lütkepohl, 2005), are not considered here, while appreciating their ability to capture gradual shifts and long-run equilibrium relationships, they are not concerned with exceptional phases.

can contribute to the different steps of risk governance, the following provides an overview of their structural features and the principles that link them to real-world processes.

### 2.1.1 Structure

This section presents a simple linear VAR model with two endogenous variables and two lags, providing an illustrative example. Then, the just outlined advancements regarding IRFs, high dimensionality, and time variations are sketched.

VAR models treat each variable within a system as endogenous. Exogenous specifications are possible, though they are not typical. The VAR framework models each variable as a linear function of its own past values and the past values of the other variables in the system. As such, the model structure reflects a dynamic network in which past values propagate through interconnected channels over time. Let $y_{1t}$ and $y_{2t}$ denote two jointly endogenous time series variables observed over time. While the following example illustrates a bivariate VAR model of order 2, both the number of variables and the lag length can be freely specified to suit the empirical context.

$$y_{1t} = c_1 + \sum_{k=1}^{2} \big(a_{11,k} y_{1,t-k} + a_{12,k} y_{2,t-k}\big) + u_{1t},$$
$$y_{2t} = c_2 + \sum_{k=1}^{2} \big(a_{21,k} y_{1,t-k} + a_{22,k} y_{2,t-k}\big) + u_{2t},$$

where $c_i$ are intercept terms and $a_{ij,k}$ are autoregressive coefficients capturing the effect of variable $y_j$ on variable $y_i$. The indices $i, j \in \{1, 2\}$ refer to the two endogenous variables, and $k \in \{1, 2\}$ denotes the lag order. The residuals $u_{1t}$ and $u_{2t}$ are assumed to be white noise and may be contemporaneously correlated (Sims, 1980; Stock and Watson, 2001; Kilian and Lütkepohl, 2018).

The results of VAR models are typically illustrated using IRFs, which show the model's reaction to a shock in one variable. As rolled out, depending on the purpose of the modeling and the correlation in residuals, further modeling of the error terms can be reasonable to obtain different IRFs. Standard IRFs ignore correlation in residuals by setting $u_{1t} = \delta_1$ and $u_{2t} = 0$ for a shock

$\delta_1$ to $u_{1t}$. Orthogonalized IRFs attribute the correlation in residuals to one variable, assuming contemporaneous causality. The most prominent approach is to orthogonalize the covariance matrix of residuals using the Cholesky decomposition,[4] which yields the Cholesky impact matrix $S$, as shown in Table 1. A shock to the first variable results in residuals $u_{1t} = s_{11}$ and $u_{2t} = s_{21}$, while a shock to the second results in $u_{1t} = 0$ and $u_{2t} = s_{22}$ (Sims, 1980; Lütkepohl, 2005). Note that the epistemological rationale for this will be covered in the next section. Finally, Generalized IRFs retain the reduced-form structure and account for residual correlation by displaying the average comovement conditional on a one-standard-deviation shock to one variable: if $u_{1t}$ is shocked by its standard deviation $\sigma_1$, then $u_{1t} = \sigma_1$ and $u_{2t} = \sigma_{12}/\sigma_1$ (Pesaran and Shin, 1998).[5]

| **Covariance matrix of residuals :** | **Cholesky impact matrix:** |
|---|---|
| $\Sigma_u = \begin{pmatrix} \sigma_1^2 & \sigma_{12} \\ \sigma_{12} & \sigma_2^2 \end{pmatrix}$ | $S = \begin{pmatrix} s_{11} & 0 \\ s_{21} & s_{22} \end{pmatrix}$ |

Table 1: Comparison of the residual covariance matrix $\Sigma_u$ and its Cholesky decomposition $S$, where $\Sigma_u = SS'$. The covariance matrix $\Sigma_u$ captures the empirical variances and covariances of the reduced-form residuals $u_{1t}$ and $u_{2t}$. The lower-triangular Cholesky matrix $S$ maps orthogonalized shocks to these residuals while preserving their contemporaneous covariance structure.

Finally, shifting the focus to regime-dependent dynamics, both Markov Switching VAR and Threshold VAR models assign a discrete regime index to all coefficients, allowing for abrupt and state-contingent changes in system behavior (Tong and Lim, 1980; Hamilton, 1989; Krolzig, 1997).

[4]This procedure transforms the covariance matrix of residuals into a structural matrix with a lower triangular form, in which all elements above the diagonal are set to zero. Accordingly, the first variable is contemporaneously affected only by its own structural shock. The second variable, by contrast, can be contemporaneously influenced by both the first variable and its own shock, but not by any variable ordered after it. This recursive structure extends to all subsequent variables in the system (Sims, 1980; Lütkepohl, 2005).

[5]If the first reduced-form residual $u_{1t}$ takes the value $\sigma_1$, the expected value of the second residual $u_{2t}$ is given by $E[u_{2t} \mid u_{1t} = \sigma_1] = \mathrm{Cov}(u_{1t}, u_{2t}) / \mathrm{Var}(u_{1t}) \cdot \sigma_1 = \sigma_{12}/\sigma_1$. This reflects the conditional mean response of $u_{2t}$ to a one-standard-deviation realization of $u_{1t}$, based on their contemporaneous covariance structure (Pesaran and Shin, 1998).

### 2.1.2 Relation to reality

Applying VAR models in risk governance necessitates carefully considering their relation to the complexities of the real world. The principles guiding variable selection and the approach to analyzing their relationships differ subtly, shaped by the specific aims of the study. The model design and hence the variable selection should be theory-driven to ensure relevance and interpretability, in statistical analysis, generally (Box, 1976). Further, for modeling purposes, it is crucial to decide on the number of variables to consider. Box (1976) drawing on Occam's razor[6] advocates for parsimonious models, claiming that they reflect stronger scientific reasoning than overly complex ones. Occam, of course, aimed to provide explanation and understanding; however, large models and data sets better depict complex systems and can contain crucial second-order patterns (e.g., interactions or rare events). Hence, in the domain of risk governance, both approaches can be valid, considering complexity is crucial for oversight (Renn et al., 2011). With that in mind, when selecting variables, there are always two risks. First, choosing too few, omitting relevant variables (Lütkepohl, 2005; Yule, 1926). Second, choosing too many variables, risking that, as the number increases, the number of parameters to be estimated skyrockets, making estimation increasingly challenging (Lütkepohl, 2005).[7]

Further, choosing an appropriate number of lagged observations in the VAR model is essential for capturing the temporal dynamics among the variables. The optimal number of lags may vary depending on the frequency of the data and the speed of adjustment in the underlying processes. Statistical procedures such as the Akaike information criterion, the Bayesian information criterion (also referred to as the Schwarz criterion), the Hannan–Quinn information criterion, and sequential likelihood ratio tests guide selecting the lag order (Lütkepohl, 2005; Ivanov and Kilian, 2005).

The integrity of the data and its conformity to the model's assumptions are of central importance. Standard VAR models require the underlying processes to be stationary (Lütkepohl, 2005). Stationarity implies that the statistical properties of the time series, such as the mean,

[6]Occam's Razor, attributed to the 14th-century English philosopher and theologian William of Occam, is the principle that among competing explanations with equal predictive power, the simplest one should be preferred (Tornay, 1938).

[7]To address this issue, in high-dimensional setups, Bayesian estimation techniques have become standard practice (Lütkepohl, 2005; Chudik and Pesaran, 2016).

variance, and autocorrelation structure, remain constant over time. To verify this condition, it is advisable to apply unit root tests, such as the Augmented Dickey-Fuller test and the Kwiatkowski-Phillips-Schmidt-Shin test. Suppose evidence of non-stationarity or structural breaks is found. In that case, the data should be transformed appropriately, for example, through differencing, de-trending, logarithmic scaling, or seasonal adjustment, to ensure that the model assumptions are satisfied and reliable inference is possible (Wooldridge, 2009). In addition, as aforementioned, there are also modeling approaches that allow for accounting for structural breaks, e.g., due to business cycles in macroeconomic analysis or volatility clustering in finance in data (Hamilton, 1989; Krolzig, 1997).

A key challenge in statistical analysis is to distinguish correlation from causation. When researchers aim to give structural meaning to observed correlations, they encounter the identification problem. As noted by Haavelmo (1944), the joint distribution of observed variables captures statistical patterns but does not alone reveal structural causal links. One widely used approach to explore causal relationships is Granger causality[8]. This method provides insights into predictive causality by testing whether past values of one variable improve forecasts of another.

This identification problem becomes particularly pressing when illustrating the results of a VAR model with IRFs. An IRF is designed to trace the effect of a single, isolated shock (structural shock that is mutually independent of other shocks) to one variable. If the model's residuals are correlated, a shock to one variable rarely occurs in isolation, it typically coincides with shocks to other variables. For sound interpretation and illustration of shock dynamics with IRFs, there are multiple identification strategies, all building on restrictions of the model based on theoretical assumptions. The most classical one is the Cholesky decomposition, which imposes a causal linear hierarchy among the variables (Sims, 1980; Lütkepohl, 2005).[9] [10] Yet, as the choice of variable ordering in a Cholesky decomposition may bias results, and the si-

[8]This concept of causality is purely predictive and does not necessarily imply a structural or instantaneous causal relationship. The standard approach involves estimating two models, one with only lags of $Y$ (restricted), and one with lags of both $Y$ and $X$ (unrestricted), and assessing whether the inclusion of the lags of $X$ significantly improves model fit (Granger, 1969).

[9]Note that there are further approaches, such as sign restrictions, but a detailed review of these procedures is beyond the scope of this work.

[10]An excellent example of this analysis can be found in Mateane et al. (2025), who study the effects of aggregate demand shocks in Germany.

multaneous occurrence of shocks can be analytically relevant, particularly in the context of risk governance, Generalized IRFs provide a compelling, ordering-invariant alternative. Rather than ignoring correlations among residuals, Generalized IRFs account for them by tracing the effect of a shock to one variable while incorporating the expected contemporaneous responses of other variables, based on the historically observed covariance structure of the residuals (Pesaran and Shin, 1998). These properties make them especially suitable when structural ordering is ambiguous, a situation frequently encountered in exploratory studies or high-dimensional systems (Pesaran and Shin, 1998; Kim, 2013). As a result, Generalized IRFs are widely used in applications such as contagion and spillover analysis in economics (Pesaran and Shin, 1998; Ehrmann et al., 2003) and finance (Diebold and Yilmaz, 2012; Zopounidis et al., 2021).

### 2.1.3 Support of Risk Governance

Moving on, it is delineated how VAR models contribute to the selected steps of the ISO risk governance process. In his foundational paper, Sims (1980) outlines several purposes for employing VAR models in macroeconomic analysis, such as forecasting, policy analysis, and testing economic theory. While these objectives remain central to empirical macroeconomic research, methodological innovations have further extended the analytical capabilities of these models, particularly in the context of risk governance.

At the outset, VAR models are empirical tools to quantify dynamic relationships among time series. The results are typically displayed using either Standard, Orthogonalized, or Generalized IRFs, which all reveal the magnitude and paths of propagation and hence interaction structures, when shocking singular system variables. They all answer the question ”How much (co)movement can be expected when a univariate shock occurs?”. Yet they treat potential correlations among residuals differently, yielding slightly different inference statements. Standard IRFs display the case of no correlation in residuals, adding ”under the assumption of no correlation among residuals”. Orthogonalized IRFs account for the correlation of residuals and attribute it to a specific variable, assuming a straight causal chain, which facilitates the interpretation of dynamic interactions (Sims, 1980). Generalized IRFs provide clear pictures of expected comovement by accounting for average historical correlation among residuals (Pesaran and Shin, 1998). Generalized IRFs for high-dimensional VAR extensions, such as Global VARs (Chudik and Pesaran, 2016) and Network VARs (Mlikota, 2022; Ahelegbey et al., 2021), can be interpreted as stress testing. Therefore, IRFs help to understand the consequences of shock scenarios by showing when and to what extent each variable responds.[11] This provides valuable insights for the *risk identification* and *risk analysis* steps in risk governance. Additionally, as highlighted by Sims (1980), Orthogonalized IRFs can also be used to test economic theories. Even deeper insights are provided by Granger causality tests. Both approaches offer a more detailed understanding of causal relationships. This not only enhances the *risk analysis* process but also helps identify the relevant factors for defining the *scope and context* of the risk governance framework.

Additionally, Sims (1980) also touches on the possibility of exploring hypothetical policy scenarios in the VAR model, simply by shocking respective variables in the model, e.g., interest rates. This fosters the understanding of potential effects and hence supports the selection and design of *risk treatments*. However, likewise, VARs provide a quantified understanding of the effectiveness ex-post of implemented policies, contributing to *risk analysis*. In addition, the ex-post policy analysis can naturally inform future policy, as insights can also be drawn for improving the *treatment of risk*.

Ultimately, VARs are valuable forecasting tools. They use the last observed data as lagged inputs within the autoregressive structure and iteratively project future values for each subsequent time step (Sims, 1980). Network VARs and Global VARs refine these forecasts by embedding them within explicit cross-sectional structures, ensuring that projections reflect the true complexity of networks or international linkages and enabling forecasts on a more granular level (Pesaran et al., 2009; Mlikota, 2022). Due to the forecasts, it is possible to foresee when and where risk criteria are likely to be exceeded and, accordingly, provide valuable information for *risk analysis* and in turn for *treatment of risk*, as this can guide preemptive measures and corresponding further information collection.

Policymakers should, as a matter of principle, critically reflect on model-based insights. Em-

[11] Our study Sheenan et al. (2025), presented as the third chapter of this dissertation, serves as a clear example of such an application.

pirical investigations are typically grounded in specific spatial and temporal contexts and may diverge from the particular realities that policymakers face. Models with thresholds or Markov-switching structures offer improved flexibility in capturing varying market conditions, potentially enabling more meaningful comparisons (Krolzig, 1997). Empirical models should be applied to alternative datasets to conduct additional robustness checks, which provide valuable out-of-sample indicators of their generalizability (Wooldridge, 2009). Nonetheless, empirical methods are inherently retrospective, and given the continuous evolution of real-world conditions, the specific circumstances policymakers encounter may ultimately differ from those captured in the model (Charpentier, 2008).

## 2.2 Input-Output Analysis

Before proceeding to specific details, let us explore the broader horizon of IOA. The term does not refer to a single method, but rather to all methods used for the analysis of input–output (IO) tables. These network maps represent economic or financial structures within a specific geographical scope for a particular period. IOA can be seen as a specialized field in the transdisciplinary domain of network analysis. While, when classical network analysis methods are applied on IO tables, this also constitutes IOA (An et al., 2024).

For the analysis of the economy, there are different types of IO tables varying in their geographic scope, e.g., international or national, and granularity level, e.g., country, region, firm, or commodity.[12] IO tables also differ in their units of account, being measured in monetary terms, physical units, or a combination of both. Extensions include, e.g., Environmentally Extended IO tables, which add environmental flows such as emissions or waste. In IOA, the standard demand-driven Leontief model relates sectoral gross outputs to final demand, whereas the supply-driven Ghosh model connects gross production to primary inputs. Alternatively, supply-driven settings can be captured by modifications of the Leontief framework (Miller and Blair, 2021). While IOA originated in production and trade economics, its applicability has since expanded to include finance. Financial IO structures have been proposed to represent relations among banks or between countries, with rows and columns denoting financial insti-

[12]For the sake of illustration and simplicity, moving forward, I will refer to sectors.

tutions or nations (Aldasoro and Angeloni, 2013; Cheng and Zhao, 2019; Elliott et al., 2014; Schuhmacher, 2019). In traditional IOA, the use of multiplier models to evaluate the system-wide impacts of changes in exogenous components is standard practice. These models quantify how shocks propagate through the system by linking exogenous changes to endogenous responses across sectors via the Leontief inverse. Typically, the Leontief quantity model with final demand shocks is used to study the impact on outputs. Effects may capture various layers of economic interactions, including direct and higher-order effects (Miller and Blair, 2021; United Nations et al., 2022). Similarly, in financial IOA, the Leontief inverse captures how a funding shock originating from a single institution or sector can ripple through the broader financial network (Cheng and Zhao, 2019; Elliott et al., 2014). In addition, there are dynamic IO models and Computable General Equilibrium (CGE) models, long-standing, traditional tools in quantitative policy analysis, that are computational evolutions based on difference equations of IOA. Another computational IO-based method is Stochastic Actor-Oriented Modeling.[13] However, these computational methods are beyond the scope of this subsection. Subsequently, I will focus on approaches based on static IO tables and not based on difference equations.[14] To base the discussion on the strengths of IOA in contributing to different steps of the risk governance process, subsequently, first, a background on the structural characteristics and the principles by which the models relate to reality is laid out.

### 2.2.1 Structure

As outlined above, there are various types of IO tables and models. For the sake of illustration, a rudimentary sketch of an IO table is presented where final demand is aggregated into a single

[13]However, works using Stochastic Actor-Oriented Models, such as those studying how production chain links are formed (e.g., Mundt (2021)), are very interesting in the light of resilience, as they provide insight into adaptation processes after disruptions.

[14]Also, there are CGE models based on static IO tables; I exclude them from this review, focusing on methods that closely align with my practical experience. However, more recent IO models, in particular, CGE models incorporate altered behavioral assumptions; see, for example, Liu and Tsyvinski (2024), Pichler et al. (2022), and Diem et al. (2022, 2024a). Since these computational frameworks feature interacting entities, they represent a methodological convergence with ABMs. Consequently, this study interprets these frameworks more broadly as ABMs and includes them in the corresponding section. A personal communication with Giacomo Livan supported this interpretation during his visit for the Research Training Group workshop on "Complex Networks and their Applications" in Bamberg. This classification is further substantiated by the work of Marco Pangallo and Maria del Rio-Chanona, who, while co-authoring a study presented as a dynamic input-output model in Pichler et al. (2022), refer to the same project as an ABM in another co-authored publication (Pangallo and del Rio-Chanona, 2024).

column. A basic Leontief multiplier model is then derived, building on the Leontief inverse, as this inverse is central to most IOA applications.

| | **Producers as Consumers (Intermediate Use) [Q1: Z]** | | | | | | | | **Final Demand [Q2: y]** |
|---|---|---|---|---|---|---|---|---|---|
| | Agric. | Mining | Const. | Manuf. | Trade | Transp. | Services | Other | Total |
| Agriculture | | | | | | | | | |
| Mining | | | | | | | | | |
| Construction | | | | | | | | | |
| Manufacturing | | | | | | | | | |
| Trade | | | | | | | | | |
| Transportation | | | | | | | | | |
| Services | | | | | | | | | |
| Other | | | | | | | | | |
| | **Value Added [Q3: v]** | | | | | | | | |
| Total | | | | | | | | | |
| **Total Output/Input [x]** | | | | | | | | | **Gross Domestic Product** |

Table 2: The figure shows a highly stylized representation of an input–output (IO) table, adapted from Miller and Blair (2021, p. 4). It captures the fundamental monetary flows between economic sectors over a fixed period, typically one year. Q denotes "quadrant".

The IO table is structured into three quadrants and associated totals. Quadrant 1 (upper left, matrix $\mathbf{Z}$) records intermediate transactions between sectors. For illustrative simplicity, Quadrant 2 (upper right) is shown as a single column representing the total final demand vector, $\mathbf{y}$. In practice, this quadrant is a detailed matrix typically disaggregated into components like household consumption, government spending, investment, and exports. Similarly, Quadrant 3 (bottom left, vector $\mathbf{v}$) is here represented by a single "Total" row for simplicity. This row is usually disaggregated into aspects such as employee compensation, capital income of business owners, and indirect business taxes paid to the government. Consistency requires that each sector's total input equals its total output, reinforcing the accounting identity fundamental to IOA.

The technical coefficients matrix ($\mathbf{A}$) is derived by normalizing each intermediate transaction by the total output of the receiving sector. Specifically, the coefficient $a_{ij}$ represents the amount of input from sector $i$ required to produce one unit of output in sector $j$, defined as

$$a_{ij} = \frac{z_{ij}}{x_j}, \tag{1}$$

where $z_{ij}$ is the flow from sector $i$ to sector $j$ and $x_j$ is the total gross output of sector $j$. The construction of $\mathbf{A}$ assumes fixed input proportions, reflecting a Leontief-type factor production function without substitution between inputs. The dependencies embedded in $\mathbf{A}$ form the basis for the Leontief inverse. The output requirements can be expressed in matrix form as

$$\mathbf{x} = \mathbf{A}\mathbf{x} + \mathbf{y}, \tag{2}$$

indicating that total output ($\mathbf{x}$) must meet both intermediate ($\mathbf{A}\mathbf{x}$) and final demands ($\mathbf{y}$). Recursively substituting $\mathbf{x}$ yields higher-order dependencies: $\mathbf{A}(\mathbf{A}\mathbf{x})$ captures inputs required to produce the intermediate inputs, $\mathbf{A}(\mathbf{A}(\mathbf{A}\mathbf{x}))$ captures inputs needed for second-order production, and so forth. This iterative process results in an infinite geometric series:

$$\mathbf{x} = (\mathbf{I} + \mathbf{A} + \mathbf{A}^2 + \cdots)\mathbf{y} = (\mathbf{I} - \mathbf{A})^{-1}\mathbf{y}. \tag{3}$$

Under standard convergence conditions, the series converges as shown. The matrix $\mathbf{L} := (\mathbf{I} - \mathbf{A})^{-1}$ is the Leontief inverse, so the demand-driven IO model is simply $\mathbf{x} = \mathbf{L}\mathbf{y}$, where $\mathbf{L}$ captures all direct and indirect output requirements needed to satisfy a given final demand $\mathbf{y}$ (Miller and Blair, 2021).

### 2.2.2 Relation to Reality

The given example shows an IO table and Leontief multiplier model that representatively demonstrate how the structure of IO tables firmly guides variable selection and the design of the relations among them in IOA.

In this context, it is worth bearing in mind that IO tables are constructed representations of economic reality. Compiling these tables involves many methodological decisions when harmonizing and balancing from different sources (Christ, 1955; Australian Bureau of Statistics, 2000; Miller and Blair, 2021; Gretton, 2013). These steps require methodological discretion that renders IO tables susceptible to the assumptions embedded in their construction (Gretton, 2013).

In an early critical review, Christ (1955) outlines four key simplifying assumptions in IOA, which cover the design of the tables and the behavioral assumptions in the analysis. Before delving into behavioral factors, I will review the sector homogeneity assumption, which serves as the foundation for sector aggregation, a particularly critical aspect of IO table construction. The granularity at which industries are defined has direct implications for both the explanatory power and the internal consistency of the model. Aggregation is often not only a practical concession but a necessary step due to limitations in data collection. Disaggregated data, especially concerning secondary products or cross-industry flows, are generally unavailable at sufficient resolution (Kymn, 1990; Australian Bureau of Statistics, 2000; Miller and Blair, 2021). Moreover, confidentiality requirements must be respected, especially in narrowly defined sectors where detailed disclosure could reveal sensitive firm-level information (Australian Bureau of Statistics, 2000).

Furthermore, even after construction, IO tables can require simplification for analytical purposes. Computational burdens increase substantially with the size of the matrix, making disaggregated models difficult to handle in practice. This was especially historically the case, see e.g. Christ (1955) or Miller and Blair (2021). Additionally, Clouse (2023) argues, aggregated models often strike a pragmatic balance between empirical tractability and communicative clarity, especially in policy contexts.

Nevertheless, the simplifications inherent in aggregation are not without epistemological cost, especially in sectors characterized by high degrees of heterogeneity or complex product mixes (Kymn, 1990; Miller and Blair, 2021). Aggregation thus risks introducing bias by masking technological diversity and averaging structurally distinct processes. This is particularly problematic when using satellite data, for example in Environmentally Extended IO models, where alignment with granular geographic data is essential for accurately attributing environmental burdens (Lenzen, 2010). More granularity offers considerable advantages in this regard. They also enable the identification of key sectors, which is critical for both impact analysis and resilience studies (Kymn, 1990).[15]

As stated earlier, a further epistemological concern lies in IOA's behavioral assumptions. Most notably, the Leontief production model assumes fixed input coefficients, meaning industries

[15]There are several approaches to handle aggregation bias in IOA. Methods such as first-order bias approximations, entropy-based information loss metrics, and mixed-product or commodity-by-industry frameworks are reviewed in detail by Kymn (1990). Each approach introduces additional assumptions and complexity; a full review of these methods is beyond the scope of this study.

use inputs in unchanging proportions, regardless of prices or technological advances (Christ, 1955; Miller and Blair, 2021; Clouse, 2023). This excludes substitution effects and endogenous efficiency gains, despite their central role in real-world production dynamics (Christ, 1955). Moreover, IO models typically assume constant returns to scale, ignoring economies or diseconomies that may arise as production expands or contracts (Christ, 1955; Miller and Blair, 2021; Clouse, 2023).

Additionally, classical IO models assume unlimited input availability and fixed prices, effectively excluding supply-side constraints and budget limitations. As a result, they neglect displacement effects, resource competition, and behavioral adaptation, all of which are central to real-world economic adjustment processes (Clouse, 2023; Gretton, 2013).

These structural assumptions also imply a static analytical framework: IOA models represent the economy at a single timespan in time and treat technical coefficients as invariant to policy shifts, price changes, or external shocks (Miller and Blair, 2021; Christ, 1955). This static orientation limits the applicability of IOA for long-term or large-scale policy analysis. As Denniss (2012) emphasizes, IOA is most appropriate for small, marginal changes and loses coherence when applied to dynamic or path-dependent developments.[16]

### 2.2.3 Support of Risk Governance

The subsequent discussion details how IOA assists in the selected stages of the ISO risk governance process. IOA offers a multitude of valuable insights for risk governance in the real economy and financial sector. First of all, it has improved the fundamental understanding of the economy and its network dynamics inside it, and thereby the importance of network effects and network structures for aggregate dynamics (Acemoglu et al., 2012; Schulz et al., nd; Barrot and Sauvagnat, 2016). In this manner, it has helped to amplify the *scope and context* that is taken into consideration for economic policy in the first place. Further, IOA allows for the uncovering of structural patterns associated with risks. Network analysis, primarily through centrality measures, is commonly used to detect critical nodes, both in production systems (e.g., Carvalho et al., 2021; Diem et al., 2024b; Chakraborty et al., 2024) and in financial net-

[16] As mentioned above, dynamic IO models and CGE models are beyond the scope of this study, unless they are extended in a manner that they can already be considered an ABM.

works (e.g., Aldasoro and Angeloni, 2013; Elliott et al., 2014). In a similar way, dependencies or exposures can be identified using static IO multiplier models. This is done by introducing changes in certain magnitudes, such as a price shock to a specific sector, and observing how these changes propagate through the system. The approach allows for quantifying both direct and higher-order effects of such shocks. Our work (Ipsen et al., 2025), presented in the third chapter of this dissertation, provides a representative example. Similar analyses are conducted in studies focusing on the real economy (Diem et al., 2024a; Chakraborty et al., 2024) and in the financial sector (Aldasoro and Angeloni, 2013; Cheng and Zhao, 2019). Also prominent is Environmentally-Extended IOA, which supports risk governance by identifying exposures to environmental impacts across regions, economic sectors, and supply chains (Kitzes, 2013). In this manner, IOA contributes to multiple steps of the risk governance process. First, by quantifying connectedness and risk exposure, it locates risk patterns and contributes directly to *risk identification*. In addition, the understanding of connectedness and propagation paths, as well as quantified risk exposures, gives an outlook on the potential severity of consequences, both contributing to *risk analysis*. Building further on this, IOA can help to define and optimize the *scope and context* under consideration or adjust the focus. In the same vein, it can support the step of *risk treatment* by guiding appropriate measures, either in the form of responses to address risk exposure or by encouraging additional data collection and monitoring that go beyond the scope or resolution of the available data. This can also entail the decision to raise the evaluation frequency or even establish early warning systems close to the location of the relevant risk factors. Finally, another manner in which IOA can support *risk treatment* is the use of multipliers to evaluate policy scenarios and gauge their potential disruptive impact.[17]

Of course, policymakers should always keep in mind how the model and its results relate to reality. Limitations of methods relying on static IO tables have been laid out. Analysis relying on static IO tables has simple behavioral assumptions, while in my view, these are not limiting the qualitative identification of dependencies or exposures; quantitative shock impact gauges of multipliers should be cautiously interpreted. Further, biases through aggregation and the

[17]Note that there are valuable works using dynamic IOA setups to assess risk mitigation strategies, see e.g., Barker and Santos (2010); Jin and Zhou (2023).

non-homogeneity of sectors should be kept in mind. Hence, I regard the distinctive capacity of static IOA to locate risk sources as its principal strength. Of course, this also highlights the importance of using data that is as up-to-date and granular as possible.

## 2.3 Agent-Based Models

Let us begin by exploring the terrain that encompasses ABMs. They constitute a highly heterogeneous class of models and differ in form, validation strategies, and intended purposes, and as a result, they are also categorized in diverse ways. For instance, Axtell and Farmer (2025) propose a size-based typology, distinguishing between small-scale models (including reduced-form models), medium and large-scale models (including full-scale models). Another approach, offered by Sun et al. (2016), classifies ABMs according to their epistemological function, differentiating between ”proof-of-concept” models and ”photograph” models. The former explains mechanisms and emergent phenomena (e.g., stylized facts) in generalized settings, the latter is grounded in case-specific data and allows for context-sensitive inferences.[18] This already points to a broader insight: both the structural design of an ABM and the way it is related to empirical reality depend highly on the model's intended purpose (LeBaron and Tesfatsion, 2008; Gräbner, 2018). Epstein (2008) provides an extensive but non-exhaustive list of model purposes, which Edmonds et al. (2019) condenses to ”prediction, explanation, description, theoretical exploration, illustration, analogy, and social learning” (p.2). Noteworthily, the first ”prediction” is a relatively recent innovation related to photograph-type models in economic ABMs (Axtell and Farmer, 2025). Subsequently, the structural characteristics, the principles to relate the model to reality, and the potential of ABMs to contribute to different steps of the Risk governance process are laid out.

### 2.3.1 Structure

Since ABMs are very heterogeneous in their design, I abstain from giving an example and instead lay out the fundamental concepts. ABMs, as the name suggests, are centered around the idea that the economy consists of heterogeneous, interacting agents (Epstein and Axtell, 1996).

[18]When using these terms he refers back to Janssen and Ostrom (2006) for ”proof of concept” and for ”photograph” to Parker et al. (2003).

Most ABMs that explicitly account for this by modeling agents as entities; yet, there are also reduced-form ABMs that account for complexity by interpreting the representative agent as a representative population that can behave in different ways, and whose mechanisms still resemble the required complexity (Lux, 2018). Agents' behavioral rules and resources determine how they affect other agents or environmental variables, and are in turn affected by different agents or environmental variables. Variables' direct interrelations can be one-way or bidirectional, with interaction mechanisms and, hence, causalities being specified. Due to the dynamic updating, the models are inherently time-varying (Turrell, 2016; Sun et al., 2016; Tesfatsion, 2017; Axtell and Farmer, 2025). Dynamics are mainly endogenous, yet exogenous variables can be reasonable depending on the ABM purpose, e.g., in scenario analysis or forecasting purposes (Axtell and Farmer, 2025; Pangallo and del Rio-Chanona, 2024; Tesfatsion, 2017).

### 2.3.2 Relation to Reality

Tesfatsion (2017) portrays four forms of model validation: input validation, process validation, descriptive output validation, and predictive output validation.[19]

Input validation assesses whether the model is capable of representing the relevant aspects of the system under investigation at the initial state (t = 0) in a manner that is sufficiently consistent with their real-world counterparts. The first step is to identify and classify the types of agents, determine the number of each agent type (scale of the model), and assess their relevance to the macroeconomic phenomena being studied. Behavioral determinants (motivation, capacities, and limitations). The map of structural relations and the nature of relations (functional forms) are coined by behavioral factors. They are based on evidence from field studies, econometric studies, experiments, surveys, and interviews (LeBaron and Tesfatsion, 2008; Tesfatsion, 2017; Gräbner, 2018; Sargent, 2010; Steinbacher et al., 2021). If the aim is to model a specific economy, IO tables, census data, and business registries can be used (Poledna et al., 2023; Wiese et al., 2024). The conceptual model's design can be validated by ensuring it is based on well-

[19] In ABM literature, the terms verification and validation are often used interchangeably, with their meanings frequently blurred. Building on the distinction proposed by Balci (1997), I understand verification as the process of ensuring that the model has been correctly implemented, while validation refers to the extent to which the model provides an adequate representation of the real-world system it aims to simulate. Subsequently, I focus on validation as the evaluation of a model's ability to capture the essential dynamics of the target system.

established theory (Sargent, 2010). Depending on the modeling goal, it is essential to balance two principles: KISS ("Keep It Simple, Stupid"), which advocates for minimalism to enhance clarity and analytical tractability (Axelrod, 1998), and KIDS ("Keep It Descriptive, Stupid"), which emphasizes capturing the richness and complexity of real-world behavior (Edmonds and Moss, 2004).

Process validation evaluates whether a model's internal logic plausibly reflects real-world processes. It focuses on the coherence, transparency, and theoretical grounding of causal mechanisms. Examples of process validation methods include expert and stakeholder review, process tracing, model walkthrough, comparison with established theory, and out-of-sample forecasting (Tesfatsion, 2017; Gräbner, 2018; Sargent, 2010).

Descriptive output validation puts the focus on whether an ABM reproduces general known empirical patterns from aggregate data (stylized facts) (Tesfatsion, 2006; Sargent, 2010; Dawid and Delli Gatti, 2018). Stylized facts that are often targets of reproduction include distributional properties and time-series behavior (Axtell and Farmer, 2025). To match real-world characteristics, models can be calibrated or estimated and graphically and/or statistically compared (Sargent, 2010; Dawid and Delli Gatti, 2018; Lux, 2018). For an extensive review of empirical estimation, see Lux (2018), Delli Gatti and Grazzini (2020), and Poledna et al. (2023). For more qualitative methods, see, e.g., Sargent (2010), among others, highlighting the degrees of freedom and hence the importance of sensitivity analysis.

Predictive output validation refers to the process of evaluating a model's ability to forecast real-world economic dynamics out of sample. These models are data-driven, meaning that real-world micro- and macroeconomic data are used to initialize agents and estimate parameters (Delli Gatti and Grazzini, 2020; Poledna et al., 2023; Wiese et al., 2024).

Concluding this subsection, it is to state that several principles and norms guide the way in designing and relating models to reality. However, there are no universal standards. ABM credibility remains contingent on a modeler's ability to demonstrate that appropriate decisions were made (Belfrage et al., 2024).

### 2.3.3 Support of Risk Governance

The following section highlights how ABMs inform the selected stages of the ISO risk governance process. Since ABMs are inherently heterogeneous, any review of their contributions to risk governance must, to some extent, account for this heterogeneity. Subsequently, the epistemologically oriented typology of Sun et al. (2016), which distinguishes between ”proof of concept” and ”photograph” models, is used due to its simplicity and suitability for discussing the contributions of heterogeneous ABMs. As laid out before, the former comprises more recent advances, while the latter refers to well-established uses.

Axelrod (2005) labels simulation, referring to ABMs as an example, as a ”third way of doing science” (p.5), adding to the well-established epistemological approaches of induction and deduction. He notes that it allows for the discovery and understanding of new relationships and principles of systems and emergent phenomena, bottom-up, from a set of rules. In other words, agent-based models are conceptual systems that offer validated representations. These models enable the theoretical exploration of mechanisms and system dynamics, such as network effects. They demonstrate how the interaction of agents through mechanisms gives rise to emergent phenomena or risks. This helps to understand how such phenomena arise, under which conditions they occur, propagation paths, and which magnitudes matter for certain dynamics (LeBaron and Tesfatsion, 2008; Bookstaber, 2012; Turrell, 2016; Dawid and Delli Gatti, 2018). Important information for risk governance, naturally for *risk analysis*, as understanding of the causes of risks is provided, but also for setting the *scope and context*. Further can already the process of conceptualization and validation uncover knowledge and data gaps and hence guide data collection (Sun et al., 2016), which is an early stage process in *risk treatment*. In addition, ABMs enable the study of the conditions for different system states in various ways, depending on their structural form. Models with analytical tractability enable the derivation of stability conditions and the creation of phase state diagrams, providing guidance on which relations are important (Gualdi et al., 2015). Numerical approaches, such as exploratory simulations that include bifurcation and sensitivity analysis, help to investigate system dynamics. They highlight how endogenous factors influence model behavior. These methods can identify critical thresholds, such as tipping or bifurcation points. Such points are crucial for understanding regime shifts and system stability (Lye et al., 2013) and thus help uncover potential emergent risks. Therefore, ABMs provide guidance on what matters for setting *risk criteria*. Furthermore, not only through exploratory but also scenario simulation, one can lead to the discovery of new risks and hence support the governance step of *risk identification* (International Risk Governance Center, 2018). Moreover, depending on their closeness to the case-specific environments that policymakers are dealing with, ABMs can put the criteria in concrete numbers. Particularly, ”photograph models”, being strongly data-driven, are able to provide insights for where and when critical events can occur in the system. Accordingly, scenario analysis and forecasting can also be used to analyse the likelihood of risks occurring (Pangallo and del Rio-Chanona, 2024; Wiese et al., 2024; Janssen and Ostrom, 2006), making data-driven ABMs a valuable tool in the step of *risk analysis*. Depending on the granularity of the supplemented spatial information, data-driven ABMs can either support *risk treatment* directly by guiding measures or suggest locations for closer monitoring beyond existing scopes and early warning indicators. Beyond that, ABMs have further valuable abilities to support *risk treatment*. They allow for exploring policy scenarios and policy mechanisms via simulation, in normal times or during crisis times. This fosters the understanding of policies, e.g., by disentangling direct effects and indirect effects, and can be leveraged to optimize the design of the policies (Westerhoff and Franke, 2018). Aminian (2025) (the second chapter of this dissertation) provides an example of this kind of work. Further examples can be found in the domain of financial stability, such as Westerhoff and Dieci (2006); Lamperti et al. (2021), and in the economy, such as in the area of transition policies Hötte (2020); Lackner et al. (2025).

Of course, also for ABMs, policymakers should always keep in mind how the model and its results relate to reality. The great versatility and complexity can make it difficult to grasp the models and consultations. Hence Belfrage et al. (2024) recommend that policymakers, or more specifically, the public administrations they represent, should involve experts to understand and evaluate ABMs and their results. In addition, Axtell and Farmer (2025) note that when stochastic terms are introduced, it is important that results are based on repeated runs with varying random seeds to test the robustness.

# 3 Discussion and Outlook

In the previous sections, the strengths and respective potentials of the approaches were laid out against the background of their characteristics. Moving on, I would like to briefly compare the special potentials of the methods and provide an outlook, describing trends that may help leverage their strengths even further, and highlight remaining challenges.

Table 3 presents an overview of the contributions of each methodological approach to the steps of the ISO 31000 risk governance process. When examining each column, focusing on the conventional forms and applications of the model types, clear patterns emerge, hinting at the individual strengths of each method, as also highlighted at the end of each subsection.
First, for ABMs, it is apparent that the perks rely on the flexibility and controllability, allowing for the exploration of various types of hypothetical setups and scenarios and beginning with model exploration through simulations, such as sensitivity analysis or bifurcation analysis, and continuing with scenario simulations that include policy treatments and forecasting simulations. A multitude of undertakings that Bankes (1993) summarizes under the umbrella term of exploratory modeling, providing an understanding of system dynamics under different conditions. Second, for IOA, it becomes clear that the unique power lies in providing qualitative information on locations, such as where risk sources and exposures are located, and where one should intensify monitoring or employ risk mitigation measures. Third, the unique strength of VAR models is to provide quantified information about the nature of the variables' relations in the past. Depending on the choice of IRFs, one can understand how a change in a variable affects another or have a benchmark for how, given a change in a variable, one can expect the others to behave in scenario analysis and forecasting exercises.
Of course, these special capacities of the classic models are to be seen in relation to the other methods, and these methods have been further developed to overcome their classical limitations. As mentioned above, it is not that IOA or VAR cannot be used to test scenarios or policies, yet they are more limited and do not allow for model exploration. IOA models suffer from simplistic assumptions regarding production functions, lack the possibility to account for factors in the model environment (such as recession/boom or bull/bear market), and effects

| ISO 31000 Risk Governance Step | ABM | IOA | VAR |
|---|---|---|---|
| **Scope, Context and Criteria** | • Model provides a theory-based causal map that can guide the focus on system areas relevant for risk governance.<br>• Exploration of system dynamics informs which variables' relations matter for the stability of regimes and the system, and hence can guide selecting and setting risk criteria. | • Mapping of network structures and identification of risk patterns can guide focus on areas relevant to risk governance. | • *(Causal)* Study of historical patterns can guide the focus on system areas relevant for risk governance. |
| **Risk Identification** | • Exploration of system dynamics to identify thresholds such as tipping and bifurcation points and thus sources for critical behavior. | • Locate risk exposures and systemically significant nodes in economic and financial networks. | • Use IRFs to identify strong propagation channels and assess interconnectedness. |
| **Risk Analysis** | • Understand system mechanisms, propagation paths, conditions for system regimes, and hence causes of emergent risks.<br>• *Scenario analysis and forecasting can help to rate the likelihood and consequences of a risk realizing.* | • Understand connectedness and propagation paths.<br>• Understand potential consequences through quantified risk exposures. | • Understand "causalities" by isolating effects with Orthogonalized IRFs and test for predictive Granger Causality, *in different regimes*.<br>• Understand risk profile by drawing on historically observed expectations of comovement via Generalized IRFs *in different regimes*. |
| **Risk Treatment** | • Use exploratory (scenario) simulations to test policy effectiveness and explore optimal mitigation strategies.<br>• *Suggest locations for further monitoring, data collection, maybe even early warning systems and further risk mitigation measures.* | • Suggest locations for further monitoring, data collection, maybe even early warning systems and further risk mitigation measures.<br>• Evaluate potential disruptions through risk treatment measures. | • Ex-post (comparative) analysis of risk treatments informing future employment of measures.<br>• Test counterfactual policy scenarios via shocks to the VAR system.<br>• *Suggest locations for further monitoring, data collection, maybe even early warning systems and further risk mitigation measures.* |

Table 3: Mapping of ABM, IOA, and VAR to ISO 31000 Risk Governance Steps. Italicized text denotes contributions that originate not from the conventional form of the approach, but from its subsequent evolutions and extensions. This table is intended to provide a concise overview, which necessarily involves simplifying compromises in both phrasing and presentation. The table does not claim to be universally applicable.

cannot be clearly attributed to specific points in time. VAR models have empirically estimated interrelations among variables, and it is possible to control, to a certain degree, the extent to which these relations depend on the model environment using time-varying models. However, given that the model does not operate bottom-up, new special circumstances or potential extreme scenarios cannot be accounted for. Additionally, ABMs and VARs can provide information on ”where in the system” by identifying variables; however, they only do so effectively if this information is attached to the data and is granular enough. An ABM would always require additional data to be aligned with, as seen in Poledna et al. (2023); Wiese et al. (2024); Pichler et al. (2023). In VAR models, the size matters, while smaller models only contain limited windows into reality. Bigger models, such as Large VAR, Global VARs, and Network VARs, can. However, to estimate these models in a reasonable manner requires additional information. For Large VARs, informed priors are used for Global VARs trade data and Network VARs network data, such as IO tables, see e.g. Chudik and Pesaran (2016) and Mlikota (2022).

Finally, ABMs and IO models have quantified variable relations based on real-world observations. However, in ABMs, there are normally high degrees of freedom, and only in strongly data-driven models, being validated on the respective model level, give a case-specific idea.[20] Similarly, IOA models provide information on interrelation, but do not allow for further derivation of what these would look like under other conditions. The relations are abstract and only found to be reasonable in the short term[21].

Accordingly, the projects in the main chapters of this dissertation provide illustrative examples of the strengths of the ”classical” forms of each method, investigating different facets of economic and financial systems. Using an ABM, I explore the mechanisms of short-selling restrictions within a generalized controlled laboratory framework, enabling me to analyze the effectiveness of containing network effects as deleveraging spirals and herding, and thus market crashes. In parallel, our IOA project provides structural insights into the EU economy, pinpointing aggregate inflation risk to critical sectors at the national level. Furthermore, the application of VAR provides estimates of relationships across high- and low-volatility regimes,

[20] Some recent ABMs claim to outperform VARs in forecasting, yet not higher-dimensional VARs. I attribute the strengths to VARs for historical reasons; looking forward, the better model approach might depend highly on data and similarity of future to modeling specifications.

[21] Without specifying this time frame, long enough for effects to realize, too short for agents to adjust behavior.

thus offering a statistical perspective on how these interactions have manifested in the past. The methods have been further developed to overcome their classical use cases and limitations. These advancements have been accounted for above and are listed and marked (in italic) in the table. When reviewing them, it becomes apparent that methods somehow adapt the strengths of other approaches. Data-driven ABMs use network and time-series data, and even employ partly Bayesian approaches to design variable selection and interrelations. Similarly, advanced IOA models are dynamic computational models with behavioral rules, so close to ABMs that they were excluded from IOA part in the above. Finally, high-dimensional VARs also integrate network structures to reduce the complexity.

Moving on, I would like to discuss how to further leverage the strengths of the methods for risk governance. To this end, I will point out what trends I observed affecting the limitations of the models and point to chances and challenges with respect to computational power, Artificial Intelligence (AI), and data availability. This discussion is guided by the understanding that, within the domain of risk governance, caution is essential. The overarching aim is to have models that enhance strategic vision (foresight and brightsight) of public administrations (International Risk Governance Center, 2018). Hence, models that offer scenario analysis and prediction, closely aligned with the case-specific reality that policymakers are dealing with, are especially valuable for risk governance. The trend to cross-integrate the strengths of other methods, as described above, appears to be motivated by the goal of improving forecasting.
Computational power is pushing the frontier of feasibility to account for more complexity. When Axtell and Farmer (2025) elaborate on the future of ABMs, they paint a bright picture, also relying on the promises of Moore's law. Moore (1965) first described the doubling of components on a chip and hence computational power annually, projecting that this exponential trend would continue. Nagy et al. (2011) study this long-term development and finds it to be even more than doubling each year, which suggests that future development could continue to accelerate, at least for a period. Ultimately, this, of course, has implications not only for ABMs but also for any computationally intensive ventures in economics and finance.
AI is revolutionizing our societies and will undoubtedly impact economic science. However,

one can expect classical econometric and statistical models to remain indispensable because their assumptions are explicit and grounded in economic theory, a feature that renders causal mechanisms transparent for regulators, policymakers, and scholars (Giudici and Raffinetti, 2023). In contrast, contemporary machine learning systems tend to achieve superior predictive accuracy only when supplied with abundant data, often of an unstructured variety. Yet, such large datasets are frequently unavailable in economics (Desai, 2023). Authentic counterfactual, or "what-if," policy investigations still require researchers to specify structural assumptions that ready-made machine learning algorithms do not inherently incorporate (Bickley and Torgler, 2022). Consequently, the most productive strategy is integration: machine learning can reveal complex and nonlinear regularities that enhance empirical evidence and forecasting, whereas classical models continue to provide interpretability and causal discipline, so that AI constitutes a complement rather than a replacement for traditional quantitative analysis (Desai, 2023).

Another crucial factor is the availability of data. Over the past decade, data availability for economic modeling has significantly improved across approaches. In agent-based modeling, household and firm microdata, together with sectoral data from IO tables and national accounts, are increasingly used for the direct initialization of ABMs (Poledna et al., 2023; Wiese et al., 2024). For IOA, granular product- and transaction-level data have become more accessible through national statistical offices and VAT data releases (Pichler et al., 2023). Furthermore, these datasets are increasingly enriched by "satellite" environmental and climate data (Pichler et al., 2023).[22] Notably, Bossut et al. (2025) explicitly called on the G20 to establish global frameworks for sharing firm-level data to boost climate resilience. VAR models have also benefited from new data sources. Text-based and sentiment data extracted from news articles and social media, using Natural Language Processing, have enhanced financial and macroeconomic risk analyses (Kalamarra et al., 2022; Du et al., 2025). The strength of this method is that it quantifies concepts that are hard to capture otherwise, as e.g., geopolitical risk (Caldara and Iacoviello, 2022), which can in turn be used in studies, see e.g., Proaño and Quero Virla (nd) or Sheenan (2023). Overall, these advances underscore the transformative potential of improved

[22]See, for example, recent initiatives by the United Kingdom Office for National Statistics to improve the timeliness and granularity of official input–output statistics (Hötte, 2025). In a personal communication (September 2025), Kerstin Hötte noted that the standard publication delay for supply and use and input–output tables is approximately three years, which limits their usefulness for timely analysis during periods of rapid structural change.

data availability for evidence-based economic policy analysis. Going forward, it can be assumed that researchers will continue to identify new data sources and develop ways to quantify and utilize them.

Concluding, I want to reflect on the given elaborations and draw some implications on the background of the motivation of this dissertation as laid out on the introduction. Namely, global challenges such as climate change and power rivalries, as well as the perceived flaws in economic modeling, in the view of former German Chancellor Olaf Scholz, as a representative policymaker. The study Olaf Scholz referred to by Bachmann et al. (2022) was subsequently criticized, among others, by Krebs (2022) for using overly simplified behavioral assumptions and for neglecting propagation effects. According to him, any credible assessment of the macroeconomic impact of a sudden stop in Russian gas imports must incorporate structural features such as empirically grounded inter-sectoral linkages and heterogeneous substitution elasticities. In this respect, I have to stress that model frameworks like this exist, see e.g., Pichler et al. (2022). Additionally, the Network VAR framework of (Mlikota, 2022), which specifies nodes based on IO tables and interlinkages based on sector price time series, might also have been a possible option. Yet, of course, ultimately the corresponding data has to be available.[23]

Bossut et al. (2025) and Pichler et al. (2023) call for more granular data, which, of course, could respectively not only be the basis for IOA but also support data-driven ABMs and Network VAR models. In supply chain management, there are already smart twin models. One can interpret them as multi-product AI ABMS. A system where each production unit in a value chain is represented and the units act based on what they learned from data (Ivanov, 2023). I believe economics will somehow move in this direction, as I expect computational limits will continue to vanish.[24] Furthermore, I believe that with the first countries providing VAT data, and given that the world is getting presumably shakier, the benefits in terms of foresight and bright-sight models accounting for more granularity and complexity will become more crystal

[23] Dunz et al. (2021) and Svartzman et al. (2021) note that future climate crisis events are likely to be unprecedented and following this, there are voices hinting that computational methods can be more appropriate (Campiglio et al., 2022; Rising et al., 2022).

[24] Of course, not every atom of the universe can be accounted for; aspects of reality must always be abstracted to serve the purpose of a model.

clear over time. Should the public interest become stronger, there will be more initiative for data. In reflecting on the broader implications of data availability for risk governance, it becomes evident that such data offer immense opportunities, but also raise significant concerns. On the one hand, granular and interconnected datasets strengthen the capacity of models to provide nuanced and accurate forecasts. Particularly under high uncertainty, thus addressing one of the fundamental challenges in economic policymaking, when facing the need to make robust decisions despite incomplete knowledge, like Olaf Scholz in 2022. The great added value of complexity-informed modeling is that it enables better decision-making under high uncertainty. On the other hand, the growing interconnectedness of data sources, especially when aggregated or linked across domains, brings privacy concerns to the fore. Misuse of data is a legitimate concern, particularly when such datasets are employed beyond strictly scientific or economic purposes. Accordingly, there have to be sound checks and balances in place. Additionally, it is paramount to note that information about dependencies can be used for both good and bad purposes, and IO tables were already utilized in World War II to guide strategic bombing (Bollard, 2019) and might also assist modern hybrid warfare. Consequently, there is an inherent tension between the promise of improved insight and the potential for infringements on confidentiality and national security. This duality underscores the need for balanced frameworks that can both harness the advantages of complex data-driven models and mitigate the associated risks. Brunnermeier (2021) and Rifkin (2022) highlight the need for society to adapt to new situations, and this includes the institutional level explicitly. For policymakers to have better consultation at hand to face presumably increasing shocks, both the ability and the responsibility lie with them. Providing access to data and funding data collection projects is a start. However, in the long run, it also matters to alter the academic landscape, from universities where researchers are trained and fundamental scientific research is conducted, to institutes and institutions for goal-oriented research. The logic is that better forecasts and scenario analysis ultimately depend on the people designing and using them, and that the development of higher-dimensional models relies on numerous scientific innovations. In this vein, Sun et al. (2016) notes that large ABMs depend on elements and mechanisms that have first been studied in small ABMs and that small models are easier to develop for new contexts.

At the core of this dissertation lies a conviction: that better decisions in times of crisis require better tools, and that communication between scientific analysis and public decision-making must be strengthened. Models do not predict the future perfectly, but they can help us to prepare for it. This work aimed to enhance preparedness by exploring how different forms of economic modeling can support risk governance. By systematically examining their structural features and relating them to institutional needs, this dissertation contributes to a more informed and purposeful use of analytical methods in economic and financial policy. In light of current global challenges, it seems all the more important to recognize and communicate what these modeling approaches can offer to society to strengthen the resilience and stability of economic and financial networks, when used with care, insight, and purpose.

# 4 Conclusion

This dissertation explored, through three projects, the applications of Agent-Based Models, Input-Output Analysis, and Vector-Autoregressive Models, each with its own contributions to economic policy-making and economic science. This concluding chapter provides further theoretical contributions. These lie in systematically reflecting upon the epistemological background of Agent-Based Models, Input-Output Analysis, and Vector Autoregressive models, and thereby provide a conceptual understanding, based on the structured framework of ISO 31000, of the strengths of complexity-based models to inform different stages of risk governance. Further, accounting for (recent) trends, it is shown how approaches have been improved, how they are possibly improving further, and how policymakers can support these developments.

Olaf Scholz's quote, as given in the beginning, hints that there is a need to level up economic methods in the face of current and arising challenges. I argue that there are complexity-based model frameworks suitable for adequate risk governance consultation, and hence, policymakers have the opportunity to improve the academic landscape (especially data availability) in a way that enables them to better address the challenges that are presumably coming.

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