SILESIAN UNIVERSITY OF TECHNOLOGY PUBLISHING HOUSE

SCIENTIFIC PAPERS OF SILESIAN UNIVERSITY OF TECHNOLOGY 2024
ORGANIZATION AND MANAGEMENT SERIES NO. 208

MULTI-DIMENSIONAL SYSTEMIC RISK MEASURE UNDER EXOGENOUS SHOCKS INCLUDING CLIMATE CHANGE

Ewa DZIWOK[1*], Witold SZCZEPANIAK[2]

[1] University of Economics in Katowice; ewa.dziwok@ue.katowice.pl, ORCID: 0000-0003-3584-1398
[2] Wroclaw University of Economics and Business; witold.szczepaniak@ue.wroc.pl,
ORCID: 0000-0002-7866-0450
* Correspondence author

Purpose: This study develops a novel methodology for measuring systemic risk through a multidimensional approach, focusing on the impact of exogenous factors. By identifying systemic risk and analysing individual risk factors, we aim to provide a more comprehensive understanding of vulnerabilities in the financial sector.
Design/methodology/approach: We use econometric models to assess systemic risk, applying our method to eight systemically important financial institutions in Poland between 2005 and 2023. Our analysis covers various risk factors, including climate risk, stock market fluctuations, and interbank liquidity, enabling both isolated and overall assessment of the impact of exogenous shocks on the system.
Findings: Our results show that climate risk is becoming increasingly significant, particularly in light of recent crises such as the COVID-19 pandemic and Russia's invasion of Ukraine. We also observe an increase in systemic risk during specific periods (2008-2009 and 2011-2013), with the impact of individual shocks varying.
Research limitations/implications: Our results highlight the need for sophisticated, multidimensional analyses of systemic risk to enhance the resilience of financial systems against diverse shocks.
Practical implications: This research contributes to the existing literature by offering a universal framework for assessing systemic risk that aggregates multiple exogenous factors, particularly emphasizing the often-overlooked role of climate risk.
Social implications: The research provides a framework for identifying systemic risks, including climate-related vulnerabilities, enabling policymakers to enhance the resilience of financial systems and protect societal stability against diverse economic and environmental shocks.
Originality/value: Importantly, we are the first to combine transition risk indicated by stranded assets with physical risk, measured by temperature deviations from the multi-year average, in the assessment of Polish systemic climate risk.
Keywords: climate risk, financial stability, systemic risk, liquidity risk.
Category of the paper: research paper.
JEL Classification: G20, Q54, C53.

1. Introduction

Systemic risk, despite its relevance to understanding financial stability, has so far not received a single, universally accepted definition. Initially, the idea (and definition) of systemic risk was associated exclusively with the financial sector, which was related to the fact that most of the crises of the 1990s originated in banks. Systemic risk was then understood as the possibility of a collapse of the (financial) system due to the failure of key financial institutions (Li et al., 2021). At the same time, the complexity of the nature of systemic risk, the interdependencies between different elements of the system, and the possible consequences in the form of a domino effect, contagion to other markets, were noticed, thus posing a significant threat to financial stability (Klinke, Renn, 2002; Renn et al., 2018).

The 2007-2009 subprime crisis and the collapse of Lehman Brothers fundamentally reshaped the understanding of systemic risk. In response, the IMF (2009) recommended analysing multiple sources of risk to obtain a more comprehensive view of potential threats. Comparative studies, including those by the European Central Bank (ECB 2010), defined systemic risk as the risk of a significant event (shock) that propagates through interconnected institutions, leading to instability across the entire system. These shocks can be either endogenous, originating within the financial system, or exogenous, caused by external factors. This dual nature further complicates efforts to consistently define and measure systemic risk.

Building on existing definitions of systemic risk, Smaga (2014), along with Montagna et al. (2020), Freixas et al. (2023), and Undheim (2024), identified several key characteristics that should be considered when developing a systemic risk measure:

- Systemic risk affects a significant portion of the financial system, making it essential to monitor critical elements, such as systemically important financial institutions (SIFIs, O-SIIs).
- Systemic risk is the effect of shocks that can originate from both endogenous (within the system) and exogenous (external) sources.
- The occurrence of shocks leading to the instability of institutions (system) requires the examination of the sensitivity of these institutions (system) to potential shocks.
- Systemic risk is characterized by the contagion effect, through which it materializes and spreads in the financial system. The pace and scale of this transmission exceeds the values that could be expected under normal market conditions (domino effect).
- The nature of systemic risk is multidimensional, requiring a comprehensive approach to measurement and management.

Defining systemic risk is further complicated by emerging challenges such as climate change. Climate risk, which includes both physical risks from environmental changes and transition risks linked to the shift towards a low-carbon economy, has become a critical component in discussions of systemic risk (BCBS, 2021; ESRB, 2021, 2022). The potential impact of climate shocks on the stability of financial markets and institutions was highlighted by Mark Carney, who emphasized the urgent need for the financial sector to incorporate climate risk into a comprehensive systemic risk framework (Carney, 2015). The effects of climate change were further amplified by the COVID-19 pandemic (Hepburn et al., 2020), accelerating the inclusion of climate risk in systemic risk measurement processes (Jung et al., 2023, Jourde, Moreau, 2024). The absence of a unified definition of systemic risk also arises from the varying perspectives of different stakeholders. Regulators primarily emphasize its potential to cause economic disruption, while market participants are more concerned with its effects on asset prices and market liquidity (Benoit et al., 2017; Giglio et al., 2021; Nguyen et al., 2023).

To address these challenges, and in line with Foglia & Angelini (2021), Hochrainer-Stigler et al. (2023), and Chen et al. (2023) we propose viewing systemic risk as a multidimensional concept that requires a comprehensive and nuanced approach to measurement. By including a broader spectrum of external risks that can contribute to systemic events – such as market (equity) shocks, climate-related risks and interbank liquidity dynamics, this approach provides an alternative tool for monitoring and managing complex financial stability risks at the systemic level. The inclusion of climate risk, including both transition and physical aspects, is particularly important as it represents an often underestimated and growing dimension of systemic risk with significant economic consequences.

In the remainder of this paper, we present our econometric methods, including the simulation of the beta risk factor for four distinct exogenous shocks and its integration into a granular fragility measure of systemic risk. Based on these simulations, we construct a composite multidimensional measure of systemic risk. Subsequently, we apply our methodology to empirical data, using a sample of systemically important banks in Poland, followed by a discussion of the results and concluding remarks.

2. MD|SRISK: multi-dimensional systemic risk measure

Benoît et al. (2013, 2017) define systemic risk as a “hard-to-define-but-you-know-it-when-you-see-it concept” and distinguish two main categories of systemic risk measures. The first category, the source-specific approach, relies on internal data from financial firms (such as risk exposures or position taken) which are primarily available to supervisory units. This approach uses existing models to separately analyse specific sources of systemic risk, such as contagion, bank runs, or liquidity shocks. The second category, the global approach, employs widely available market data to estimate the optimal level of capital necessary for financial institution withstand systemic risk events.

Initial attempts to create a composite measure focused on the source specific approach and were mainly based on stress tests (Acharya et al., 2023). While existing measures, such as the ECB's Composite Indicator of Systemic Stress (CISS) and the STAMP€ stress testing tool, have made significant contributions to assessing systemic risk, they often operate in isolation, lacking a comprehensive view of the risk landscape (Dees et al., 2017).

Our approach is based on the systemic risk measure SRISK (Brownlees, Engle, 2017; Engle, 2018) and climate systemic risk concept CRISK (Jung et al., 2023) with adaptations for different types of exogenous shocks. This methodology is inspired by established statistical measures such as SES (Systemic Expected Shortfall) from Acharya et al. (2017), and is comparable to the ΔCoVaR measure introduced by Adrian & Brunnermeier (2016). The selection of this measure is based on its ability to capture sensitivity to external events and its prior application to other (non-market) external shocks, such as transition risk.

In this context, the term "system" specifically refers to the banking system, narrowly defined as a weighted sum of systemically important institutions (according to the EBA's definition of O-SII), as noted by Benoit et al. (2017). This methodology enables the analysis of the system's sensitivity to individual shocks, both at the level of each institution and as an aggregated measure for the system as a whole.

Then, the rate of return for the system at time t, denoted by r_t can be the weighted sum of the individual rates of return of the N institutions of N institutions:

$$r_t = \sum_{i=1}^{N} w_{i,t} \cdot r_{i,t} \tag{1}$$

where:
$w_{i,t}$ represents the weight of i-th institution in the system at time t (based on e.g. market capitalization or another metric, like SIFI or O-SII scores),
$r_{i,t}$ is the stock return rate of the i-th institution,
$i = 1, \ldots, N$.

The systemic risk methodology uses publicly available market data and is based on the idea of capital shortfall CS_t defined on day t as in Brownlees & Engle (2017):

$$CS_t = \overbrace{k(D_t + V_t)}^{\text{capital reserves}} - \overbrace{V_t}^{\text{current equity}} \tag{2}$$

where:
D_t is the book value of debt for the system,
V_t is the market value of system equity,
k is the prudential capital fraction.

Negative value of the capital shortfall means that the system has a capital surplus while positive value means lack sufficient amount of capital.

The SRISK measures the potential shortfall in capital that the system would likely need if a shock (systemic event) occurs within a specified time period h:

$$SRISK_t = \mathbb{E}(CS_{t+h}|systemic\ event) \tag{3}$$

Following ECB (2010) and Acharya et al., (2017), systemic event can be broadly understood as "financial instability spreading to the extent that the financial intermediation process is impaired and economic growth and welfare suffer materially".

Formally, a systemic event is defined as the rate of return or rate of change $r_{t,t+h}^{risk\ factor} < \theta$, where θ is a shock threshold when the risk factor is in a negative trend (e.g. market shock), or $r_{t,t+h}^{risk\ factor} > \theta$ when the risk factor is in a positive trend (e.g. physical climate risk). The shock threshold can be defined as either a minimum value (for shocks in negative trends) or a maximum value (for positive trends), or as a given percentile of the historical rates of return or rates of change of the risk factor.

For simplicity, we define the system's variables as follows: $r_{t,t+h} \equiv r_t$.

An expected shortfall for shocks in negative trends is:

$$ES_t = \mathbb{E}\left(r_t | r_t^{risk\ factor} < \theta^{risk\ factor}\right) = \sum_{i=1}^{N} w_{i,t} \cdot \mathbb{E}\left(r_{i,t} | r_t^{risk\ factor} < \theta^{risk\ factor}\right) \tag{4}$$

where $\theta^{risk\ factor}$ is equal $VaR_t^{risk\ factor,q} = -F_q^{-1}\left(r_{t-h,t}^{risk\ factor}\right)$ with q being an arbitrarily chosen quantile of the distribution, and x being a return of risk factor proxy.

Following Acharya et al. (2012), the Marginal Expected Shortfall (MES) is then defined as a partial derivative:

$$MES_{i,t} = \frac{\partial ES_t}{\partial w_{i,t}} = \mathbb{E}\left(r_{i,t} | r_t^{risk\ factor} < \theta^{risk\ factor}\right) \tag{5}$$

On the other hand, an expected shortfall for the shock in positive trend is:

$$ES_t = \mathbb{E}\left(r_t | r_t^{risk\ factor} > \theta^{risk\ factor}\right) = \sum_{i=1}^{N} w_{i,t} \cdot \mathbb{E}\left(r_{i,t} | r_t^{risk\ factor} > \theta^{risk\ factor}\right) \tag{6}$$

And consequently:

$$MES_{i,t} = \frac{\partial ES_t}{\partial w_{i,t}} = \mathbb{E}\left(r_{i,t} | r_t^{risk\ factor} > \theta^{risk\ factor}\right) \qquad 7)$$

Systemic risk, as described in formula (3), is the expected capital shortfall of a system in the event of a shock, and is defined using *MES* as follows:

$$SRISK_t = \overbrace{k(D_t + (1 - LRMES_t)V_t)}^{\text{required capital}} - \overbrace{(1 - LRMES_t)V_t}^{\text{current capital}} \tag{8}$$

where Long-Run Marginal Expected Shortfall (LRMES) is the conditional expectation of a system's multi-period return on equity over a specified time horizon, given that a systemic event occurs. As a random variable, LRMES must be estimated through appropriate statistical modelling techniques (described later in the paper for each case separately).

In the extreme case of stress scenario $LRMES_t \to 1$, meaning that market capitalization falls to 0, and $SRISK_t$ reflects the system shortage of capital over chosen horizon. According to this definition, the SRISK represents the ex-ante capital buffer required to adequately withstand a financial crisis and is a function of system size, leverage and risk.

In practice, for managers, the primary concern is the shortage of necessary capital rather than any surplus. Therefore, SRISK is formulated as:

$$SRISK_t = \max\{\,0\,;\ kD_t - (1 - k)(1 - LRMES_t)V_t\,\} \tag{9}$$

In fact, the above definition (9) is universal and can be written as:

$$XRISK_t = \max\{ 0 ;\ kD_t - (1-k)(1 - LRMES_t^X)V_t\} \quad (10)$$

In this study, X represents a set of systemic shocks (risk factors) that includes four distinct types of shocks, each described by proxies. The impact of these shocks on the system is measured using the SRISK and climate CRISK metrics, with certain modifications to the latter (as shown in Table 1).

An exogenous factor, due to its mutual interdependence with the market factor, cannot be determined directly. For exogenous risks other than market risks, a method analogous to the Fama and French factor model was applied (Fama, French, 1993). In these cases, the mutual dependence between the analysed risk and market risk is considered.

Following the methodology introduced by Jung et al. (2023), the joint sensitivity of the system to compound risks S&XRISK, based on market stress and exogenous stress, is expressed as:

$$S\&XRISK_t = kD_t - (1-k)(1 - LRMES_t^X)\left(1 - LRMES_t^{M|X}\right)V_t \quad (11)$$

where $LRMES_t^X$ represents the conditional expectation of a system's multi-period return on equity over a specified time horizon, given that a exogenous event X occurs, $LRMES_t^{M|X}$ represents the conditional expectation when a market event X occurs which captures the interdependence between market shocks and external shocks. The isolated impact of an external factor is calculated under the assumption of no external shock ($LRMES_t^{M|X} = 0$) and is interpreted as the total capital injection required during stress (in isolation from the market impact), accounting for the existing capitalization of financial institutions.

Table 1.
Different types of potential shocks and their characteristics

Risk factor	Risk factor reference (proxy)	Trend of the risk factor	Measure
Market risk	Market stock index	Negative	SRISK
Transition climate risk	Stranded asset portfolio	Negative	TrCRISK
Physical climate risk	Term temperature anomaly	Positive	PhCRISK
Liquidity interbank risk	RMSE of curve-fitting model	Positive	LRISK

Source: own preparation.

Upon establishing the granular risk measures for individual exogenous shocks, the multidimensional aggregate measure of systemic risk is defined as the sum of non-negative granular risk values.

$$MD|SRISK_t = SRISK_t + TrCRISK_t + PhCRISK_t + LRISK_t \quad (12)$$

where:

$MD|SRISK_t$ is multidimensional systemic risk measure,
$SRISK_t$ is measure of system fragility for market stress scenario,
$TrCRISK_t$ measure of system fragility due to transition climate stress scenario,
$PhCRISK_t$ measure of system fragility due to physical climate stress scenario,
$LRISK_t$ measure of system fragility due to interbank liquidity stress scenario.

This methodology is sufficiently universal to integrate additional fragility measures for both external and internal stress scenarios.

2.1. Selection of references for exogenous shocks

2.1.1. Reference for the market risk

The choice of a broad stock market index as a market indicator is theoretically justified by its alignment with fundamental concepts from the Capital Asset Pricing Model (CAPM) developed by Sharpe (1964), which emphasize the importance of capturing systematic risk. Empirical studies have demonstrated that broad stock market indices, such as the S&P 500 or MSCI World, effectively capture market-wide movements and are highly correlated with the broader economy (Morgan, 1978; Bali et al., 2017). In research on local markets, the broad index of the local stock exchange is typically used.

2.1.2. Reference for the transition climate risk

To justify the choice of a proxy for transition climate risk, we aim to identify a market proxy that effectively captures this risk. One established approach, used by (Jung et al., 2023), involves constructing a portfolio based on stranded assets such as oil, fossil fuels, or coal, whose demand is expected to decline due to climate regulations such as the Paris Agreement. These industries are particularly vulnerable to transition risk, as their future profitability is expected to decrease with the shift toward carbon neutrality (van der Ploeg, Rezai, 2020; Bolton, Kacperczyk, 2021).

The stranded asset portfolio used by Jung et al. (2023), was originally developed by Litterman at WWF (Litterman, 2023), includes a 70% long position in the VanEck Coal Vectors ETF (KOL), a 30% long position in the Energy Select Sector ETF (XLE), and a short position in the S&P 500 ETF (SPY) via a total return swap (since KOL was delisted in 2021, it has been replaced by the average returns of its five largest holdings). The portfolio shows positive return when either XLE or KOL outperforms the market, and negative returns otherwise, reflecting heightened transition risk.

Alternative references (proxies) for transition climate risk can be constructed using other assets: a long position in ETFs or indices related to coal, oil and gas sectors (often referred as “brown industry” indices), and a short position in a broad market index (Reboredo, Ugolini, 2022; Semieniuk et al., 2022).

2.1.3. Reference for the physical climate risk

The term temperature anomaly, which represents deviations from long-term average temperature (typically over a 30-year period), is increasingly recognized as a reliable indicator for assessing physical climate risk. The theoretical basis for using temperature anomalies as a physical climate risk indicator stems from the assumption that unusual temperature patterns can disrupt economic activity, particularly in sectors directly dependent on climate conditions.

Since the empirical study by Cao and Wei (Cao, Wei, 2005), research by Faccia et al. (2021) Kahn et al. (2021) and Karydas & Xepapadeas (2022) has shown that weather deviations can impact economic activity, which in turn affects the financial performance of specific sectors. Other theoretical framework suggest that temperature anomalies are linked to fluctuations in stock prices (Gupta et al., 2023) and the significance of this impact has grown in recent years (Li et al., 2024). Additionally, studies by Faccia et al. (2021) Pagnottoni et al. (2022) Acharya et al. (2023) and Wu et al. (2023) highlight that temperature deviations can lead to increased risk and financial instability, particularly for banks exposed to climate-sensitive industries. While temperature anomalies play a central role in the choice of proxies for physical climate risk, other weather factors such as humidity, precipitation, rainfall, wind speed, and cloud cover are also important for identifying and managing the financial impacts.

2.1.4. Reference for the interbank liquidity risk

The significance of interbank liquidity for systemic risk was highlighted by Rochet and Tirole (1996), and the issue gained renewed attention following the 2007-2008 financial crisis, which spurred the development of new tools like stress tests (Cont et al., 2020). Moreover, Adrian et al. (2014) and Macchiati et al. (2022) emphasize the role of financial intermediaries in influencing stock returns, further linking liquidity to broader market outcomes and demonstrating the interbank market's impact on systemic risk.

Measuring interbank liquidity is particularly challenging due to mismatches errors and the difficulty of obtaining transaction-level data (Brunnermeier et al., 2014). Noise-based methods proposed by Hu et al. (2013) and Hattori (2021) offer alternative approaches for capturing liquidity dynamics. Research by Brunnermeier and Pedersen (2009) highlights that liquidity risk is closely linked to forecast accuracy, with increased forecasting errors leading to higher risk exposure. Similarly, studies by Adrian and Shin, (2010) and Adrian et al. (2017) demonstrate that inaccuracies in liquidity forecasting, reflected in high RMSE values, can negatively affect balance sheets and indicate heightened liquidity risk.

The root mean square error (RMSE) has become a tool for assessing interbank liquidity risk due to its ability to quantify the accuracy of liquidity forecasts. The theoretical basis for this application stems from the fact that RMSE measures forecasting errors, which directly reflects the stability and risk associated with liquidity management in financial institutions (Tsai, 2012).

2.2. SRISK: market systemic risk measure

For the calculation of SRISK, we define an external shock as the severe market decline, represented by the return of market stock index (as a proxy) $r_{m,t} < \theta^M$.

Following Brownlees & Engle (2017), and the V-Lab procedure utilizing the GARCH model, we estimate the Long-Run Marginal Expected Shortfall (LRMES) as follows:

$$LRMES_t^M = 1 - \exp(\beta_t^M \cdot \log(1 - \theta^M)) \tag{13}$$

where β_t^M represents the risk factor for market shocks.

To estimate beta parameter, we employ the GJR-GARCH for conditional volatility and the GARCH-DCC model to capture dynamic correlations:

$$\mathbf{r_t'} = \mathbf{H_t^{1/2}} \cdot \boldsymbol{\varepsilon_t'} \tag{14}$$

where $\mathbf{r_t'} = [r_{i,t}, r_{m,t}]$ is the transposed vector of returns at time t, and $\boldsymbol{\varepsilon_t'} = [\varepsilon_{i,t}, \varepsilon_{m,t}]$ is an i.i.d. vector with $\mathbb{E}(\boldsymbol{\varepsilon_t}) = 0$ and $\mathbb{E}(\boldsymbol{\varepsilon_t}\boldsymbol{\varepsilon_t'})$ being a two-by-two identity matrix. The matrix $\mathbf{H_t}$ is defined as:

$$\mathbf{H_t} = \begin{bmatrix} \sigma_{i,t}^2 & \sigma_{i,t}\sigma_{m,t}\rho_{i,m,t} \\ \sigma_{i,t}\sigma_{m,t}\rho_{i,m,t} & \sigma_{m,t}^2 \end{bmatrix}, \tag{15}$$

where:

$\sigma_{m,t}$ and $\sigma_{i,t}$ are the conditional standard deviation at time t for the market and the financial institution i respectively,

$\rho_{m,i,t}$ is the time-varying conditional correlation coefficient.

In this time series framework, estimating the correlation structure introduces an additional layer of complexity, particularly because of the need to account for time-varying correlations. Modelling correlations as time-varying variables allows for a more dynamic and realistic representation of the risk environment. Failure to account for the time-varying nature of correlations has been shown to result in significant negative externalities, potentially underestimating systemic risk.

2.3. TrCRISK: transition climate systemic risk measure

For the estimation of transition climate systemic risk (TrCRISK), we define an external shock as a significant transition-related disruption, modelled by the return of stranded asset portfolio (as a proxy) $r_{tr,t} < \theta^{TrC}$.

The LRMES for climate transition risks is as follows:

$$LRMES_t^{TrC} = 1 - \exp(\beta_t^{TrC} \cdot \log(1 - \theta^{TrC})) \tag{16}$$

where β_t^{TrC} denotes the risk factor related to climate transition shocks.

To assess transition climate risk we follow the procedure delivered by Jung et al. (2023) and V-Lab, and we introduce a two-factor model analogous to the CAPM. This model takes into account the asset's exposure to both market risk and a stylized climate factor representing transition risk in this case. For the market factor, we follow standard practice by using the return of a broad equity index as a proxy. For the climate factor, we adopt a stranded asset portfolio as described above. This method reflects the market's perception of climate transition risk while isolating sector-specific risk from broader market performance.

To estimate beta coefficients, we use the dynamic conditional beta (DCB) model proposed by Engle, which uses a multivariate GARCH framework with dynamic conditional correlations (DCC-GARCH) to capture the time-varying nature of these sensitivities as in formula (14) where $\mathbf{r}_\mathbf{t}' = [r_{i,t}, r_{m,t}, r_{tr,t}]$ is the transposed vector of returns at time t, and $\boldsymbol{\varepsilon}_\mathbf{t}' = [\varepsilon_{i,t}, \varepsilon_{m,t}, \varepsilon_{tr,t}]$ is an i.i.d. vector with $\mathbb{E}(\mathbf{v}_\mathbf{t}) = 0$ and $\mathbb{E}(\mathbf{v}_\mathbf{t}\mathbf{v}_\mathbf{t}')$ being a three-by-three identity matrix. The matrix $\mathbf{H}_\mathbf{t}$ is defined as:

$$\mathbf{H}_\mathbf{t} = \begin{bmatrix} \sigma_{i,t}^2 & \sigma_{i,t}\sigma_{m,t}\rho_{i,m,t} & \sigma_{i,t}\sigma_{tr,t}\rho_{i,tr,t} \\ \sigma_{i,t}\sigma_{m,t}\rho_{i,m,t} & \sigma_{m,t}^2 & \sigma_{m,t}\sigma_{tr,t}\rho_{m,tr,t} \\ \sigma_{i,t}\sigma_{tr,t}\rho_{i,tr,t} & \sigma_{m,t}\sigma_{tr,t}\rho_{m,tr,t} & \sigma_{tr,t}^2 \end{bmatrix}, \tag{17}$$

where:

$\sigma_{tr,t}$ is the conditional standard deviation of the stranded asset portfolio fragile for transition risk at time t,

$\rho_{i,tr,t}$, $\rho_{m,tr,t}$ are the time-varying conditional correlation coefficients.

In this time series framework transitioning from a univariate to a multivariate process adds an additional layer of complexity, particularly due to the need to account for time-varying correlations. Modelling correlations as time-varying variables allows for a more dynamic and realistic representation of the risk environment. Neglecting the time-varying nature of correlations has been shown to result in significant negative externalities, potentially underestimating systemic risk.

The market beta β_t^M and transition climate beta β_t^{TrC} are estimated as follows:

$$\begin{bmatrix} \beta_t^M \\ \beta_t^{TrC} \end{bmatrix} = \begin{bmatrix} \sigma_{m,t}^2 & \sigma_{m,t}\sigma_{tr,t}\rho_{m,tr,t} \\ \sigma_{m,t}\sigma_{tr,t}\rho_{m,tr,t} & \sigma_{tr,t}^2 \end{bmatrix}^{-1} \begin{bmatrix} \sigma_{i,t}\sigma_{m,t}\rho_{i,m,t} \\ \sigma_{i,t}\sigma_{tr,t}\rho_{i,tr,t} \end{bmatrix} \tag{18}$$

2.4. PhCRISK: physical climate systemic risk measure

For estimating physical climate systemic risk (PhCRISK), an external shock is defined as a deviation from a baseline or average temperature which is modelled using the return of term temperature anomaly (as a proxy) that negatively affects the system. The impact is assessed by examining cases where the temperature anomaly exceeds a certain threshold, represented by the quantile $r_{ph,t} > \theta^{PhC}$, where $\theta^{PhC} \equiv VaR_t^{PhC,q}$, with q denotes the chosen quantile of the distribution.

The LRMES for climate physical risks is then given by:

$$LRMES_t^{PhC} = 1 - \exp\left(\beta_t^{PhC} \cdot \log(\tfrac{1}{1-\theta^{PhC}})\right) \tag{19}$$

where β_t^{PhC} represents the risk factor associated with physical climate shocks.

The procedure for join estimating beta coefficients is similar to that used for transition risk, with broad market index serving as the proxy for market risk.

2.5. LRISK: interbank liquidity risk measure

To estimate interbank liquidity systemic risk (LRISK), we define an external shock as a deviation from normal interbank liquidity conditions. This is modelled using the root mean square error (RMSE) of a curve-fitting Nelson-Siegel-Svensson (Nelson, Siegel, 1987; Svensson, 1994) model applied to interbank market data, where the negative impact on the system is assessed. Specifically, we examine cases where the RMSE of the liquidity curve-fitting model exceeds a certain threshold, represented by the quantile $r_{l,t} > \theta^L$, where $\theta^L \equiv VaR_t^{L,q}$, with q denotes the chosen quantile of the distribution.

The LRMES for interbank liquidity risk is given by:

$$LRMES_t^L = 1 - \exp\left(\beta_t^L \cdot \log(\frac{1}{1-\theta^L})\right) \tag{20}$$

where β_t^L represents the risk factor associated with interbank liquidity shocks.

The procedure for estimating beta coefficients follows the same approach as for transition risk, with a broad market index serving as a proxy for market risk.

3. Empirical results of model implementation

The model was applied to the case of Poland, where it was assumed that the system consists of eight listed banks considered systemically important (O-SII): PKO BP, Pekao SA, Santander Bank Polska, ING Bank Śląski, mBank, Citi Handlowy, BNP Paribas Bank Polska, and Bank Millennium. Until 2015, the system was calculated as a weighted sum of banks' capitalization. Afterward, it was based on scores in line with the recommendations of the Polish Financial Supervision Authority (KNF) and the EBA/GL/2014/102 guidelines.

The empirical data sample spans the period from January 2005 to December 2023 and includes observations on the stock prices of the analysed banks, as well as proxies for shocks specific to the Polish market. The appendix provides descriptive statistics and indices. All data used in this article were sourced from LSEG (formerly Refinitiv Eikon).

Subsequently, the measures $SRISK_t, TrCRISK_t, PhCRISK_t, LRISK_t$ will be determined by considering external shocks (market shocks, climate transition risk, physical climate risk, and interbank market liquidity) tailored to the Polish market.

3.1. $SRISK_t$: market systemic risk measure

To measure a market shock threshold θ^M we use the broad Polish Warsaw Stock Exchange index (WIG) with $q = 1\%$, as recommended in the European Banking Authority's stress test guidance (EBA 2020). Consequently, $\theta^M = 44\%$. Figure 1 illustrates the ex-ante capital buffer (in total) that the system would likely require in the event of a shock (systemic event) within the next six months (positive values). We omit the impact of negative SRISK values, as it is unlikely that capital surplus could be easily transferred between institutions, particularly during a crisis.

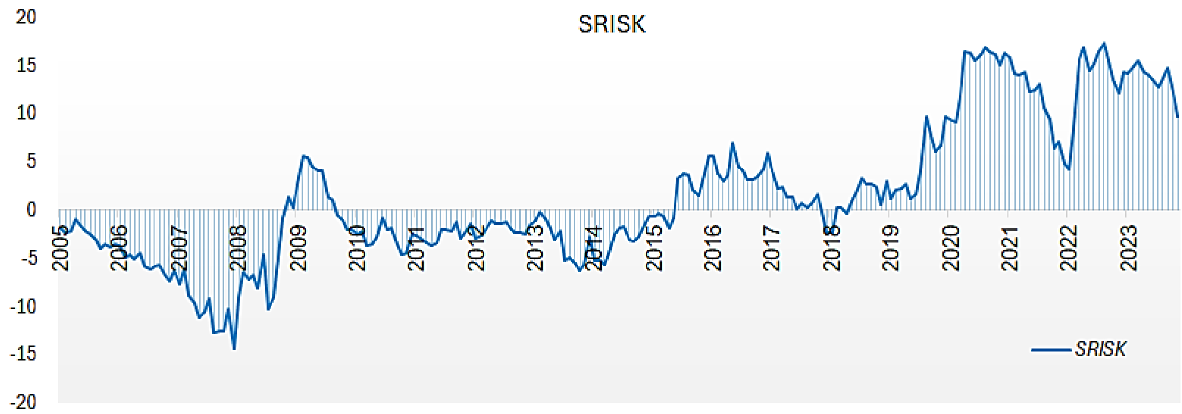

Figure 1. SRISK for Polish banking system (in bln EUR).

Source: own preparation.

3.2. $TrCRISK_t$: transition climate systemic risk measure

To capture the climate risk associated with the energy transition in the Polish market, a customised stranded assets portfolio was constructed following the approach of Jung et al. (2023). For the Polish market, the portfolio consists of a 70% long position in the WIG-mining sector index and a 30% long position in the WIG-fuels sector index, as well as a short position in a broad market index WIG. Both considered industry indices include major Polish energy and mining companies which face significant risks due to the transition to a low-emission economy. Since these indices were established on December 31, 2010 (mining) and December 31, 2005 (fuels), respectively, the earlier data was obtained using the WIG's Basic Index Algorithm Methodology (GPW, 2017).

By analysing the excess returns of this portfolio, we can estimate the climate transition risk these sectors face. A significant decline in excess returns suggests heightened transition risk, as market participants price in the decreasing profitability of these industries due to regulatory pressures and the shift towards carbon neutrality. To isolate the climate transition impact from market effects, the broad Warsaw Stock Exchange Index (WIG) is used as a market proxy.

We assume the following thresholds calculated for with $q = 1\%$: $\theta^{CTr} = 60\%$ for the climate transition risk event and $\theta^{M} = 44\%$ for the market event. Figure 2 illustrates the ex-ante capital buffer (in billion EUR) that the system would likely require in the event of a climate transition shock (isolated from the market shock) over the next six months.

The TrCRISK value captures the growing sensitivity of the banking system to losses linked to stranded assets during the COVID-19 pandemic and following the outbreak of the war in Ukraine.

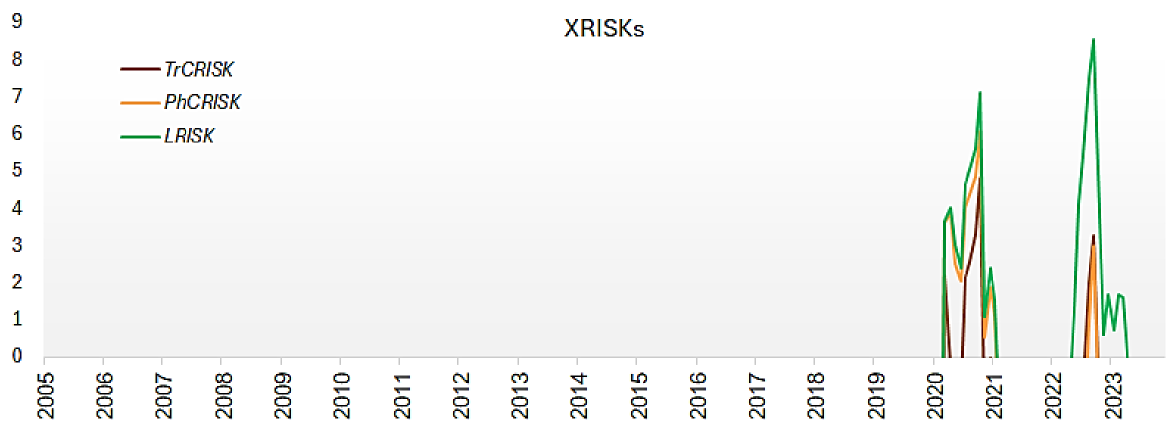

Figure 2. XRISKs measures for Polish banking system (in bln EUR).

Source: own preparation.

3.3. $PhCRISK_t$: physical climate systemic risk measure

To capture climate risk associated with physical factors in the Polish market, we used the temperature anomaly - defined as the deviation of the average annual temperature in Poland from the 30-year norm - as an external shock. Temperature data was sourced from the Institute of Meteorology and Water Management (IMiGW). We verified the significance of temperature variability's impact on systemic risk volatility using the methodology from Muhlack et al. (2022). The Long-Run MES was estimated based on the following shock levels: $\theta^{PhClimate} = 49\%$ and $\theta^{Market} = 44\%$.

During the period under review, temperature deviations from the long-term average had an increasing impact on the sensitivity of the banking system. Both the pandemic and the war in Ukraine affected the banking system's sensitivity to climate change. The war, along with the resulting energy crisis, particularly in Europe, focused market attention toward energy security and supply chain disruptions, temporarily sidelining concerns about rising temperatures (Figure 2).

3.4. $LRISK_t$: interbank liquidity systemic risk measure

For liquidity systemic risk, the interbank liquidity risk proxy was constructed using the RMSE from the Nelson-Siegel-Svensson curve-fitting approach (Dziwok, 2017). Higher RMSE values indicate larger forecasting errors and greater uncertainty in liquidity management, reflecting increased liquidity risk. Following the methodology of Jung et al., the Long-Run MES was estimated with shock levels set at: $\theta^{Liquidity} = 34\%$ and $\theta^{Market} = 44\%$, after verifying the impact of interbank liquidity variability on systemic risk volatility.

The impact of interbank liquidity risk became evident during the COVID-19 pandemic and the aggression against Ukraine. At that time, the system showed heightened sensitivity due to the increased demand for liquid funds across the entire banking sector (Figure 2).

3.5. $MD|RISK_t$: multi-dimensional systemic risk measure

Determining the system’s sensitivity to four distinct types of shocks allows us to estimate the combined impact, representing the maximum potential sensitivity of the system to these shocks (Figure 3).

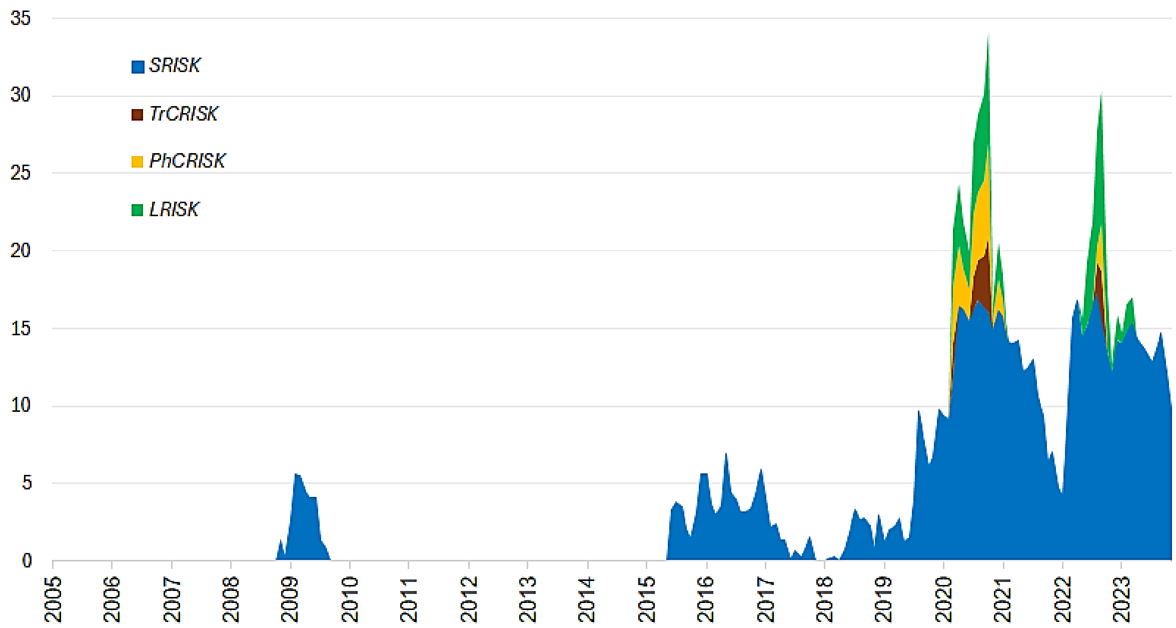

Figure 3. Multi-dimensional systemic risk measure for Polish banking system (in bln EUR).
Source: own preparation.

The study revealed that the system's response to shocks varies depending on the type of shock, although in most cases, there is a cumulative effect from multiple sources. A key factor affecting the system's vulnerability is the growing climate risk. While often overlooked in analyses of systemic risk in the Polish market, climate risk is becoming an important element that enhances system sensitivity.

4. Conclusions

The study allowed us to develop a measure to assess the sensitivity of the banking system to various exogenous shocks. With the modifications used, we were able to analyse the impact of individual exogenous shocks both in isolation and as a whole. Our methodology includes risk factors such as the stock market, climate risk and interbank liquidity.

The system's vulnerability to climate change - reflected through transition risk indicated by the stranded assets portfolio, and physical risk measured by temperature deviations from the multi-year average - proved to be a key factor. As a result, this study offers a more comprehensive analysis than previous studies conducted in Poland.

The empirical results confirmed an increase in systemic risk in Poland between 2008-2009 and 2011-2013, as well as a significant increase in risk associated with the COVID-19 pandemic and Russia's invasion of Ukraine. We also found that the impact of certain shocks varied significantly from others.

Our results confirm that systemic risk can be calculated by incorporating various exogenous shocks. This underscores the need to analyse systemic risk using sophisticated measures that highlight the nuances of the phenomenon. The results also demonstrate that the often-overlooked climate risk is a significant component of systemic risk. These results highlight the importance of analysing systemic risk in a multidimensional way, utilizing publicly available data.

Funding

Ewa Dziwok acknowledges financial support provided by the International Visegrad Fund through research project #62320216 (Visegrad Fellowship).

References

1. Acharya, V.V., Berner, R., Engle, R., Jung, H., Stroebel, J., Zeng, X., Zhao, Y. (2023). Climate Stress Testing. *Annual Review of Financial Economics*, *15*(1), 291-326. https://doi.org/10.1146/annurev-financial-110921-101555
2. Acharya, V.V., Engle, R., Richardson, M. (2012). Capital Shortfall: A New Approach to Ranking and Regulating Systemic Risks. *American Economic Review*, *102*(3), 59-64. https://doi.org/10.1257/aer.102.3.59
3. Acharya, V.V., Pedersen, L.H., Philippon, T., Richardson, M. (2017). Measuring Systemic Risk. *Review of Financial Studies*, *30*(1), 2-47. https://doi.org/10.1093/rfs/hhw088
4. Adrian, T., Brunnermeier, M.K. (2016). CoVaR. *American Economic Review*, *106*(7), 1705-1741. https://doi.org/10.1257/aer.20120555
5. Adrian, T., Etula, E., Muir, T. (2014). Financial Intermediaries and the Cross-Section of Asset Returns. *The Journal of Finance*, *69*(6), 2557-2596. https://doi.org/10.1111/jofi.12189
6. Adrian, T., Fleming, M., Shachar, O., Vogt, E. (2017). Market Liquidity after the Financial Crisis. *Federal Reserve Bank of New York Staff Reports, No. 796*. https://www.newyorkfed.org/medialibrary/media/research/staff_reports/sr796.pdf
7. Adrian, T., Shin, H.S. (2010). Liquidity and leverage. *Journal of Financial Intermediation*,

19(3), 418-437. https://doi.org/10.1016/j.jfi.2008.12.002
8. Bali, T., Engle, R., Murray, S. (2017). Empirical Asset Pricing: The Cross Section of Stock Returns: An Overview. In: *Wiley StatsRef: Statistics Reference Online* (pp. 1-8). Wiley. https://doi.org/10.1002/9781118445112.stat07954
9. Basel Committee on Banking Supervision (2021). Climate-related financial risks – measurement methodologies. *BIS. April 2021*. https://www.bis.org/bcbs/publ/d518.pdf
10. Benoît, S., Colletaz, G., Hurlin, C., Pérignon, C. (2013). *A Theoretical and Empirical Comparison of Systemic Risk Measures*. https://shs.hal.science/halshs-00746272v2
11. Benoit, S., Colliard, J.-E., Hurlin, C., Pérignon, C. (2017). Where the Risks Lie: A Survey on Systemic Risk. *Review of Finance*, *21*(1), 109-152. https://doi.org/10.1093/rof/rfw026
12. Bolton, P., Kacperczyk, M. (2021). Do investors care about carbon risk? *Journal of Financial Economics*, *142*(2), 517-549. https://doi.org/10.1016/j.jfineco.2021.05.008
13. Brownlees, C., Engle, R.F. (2017). SRISK: A Conditional Capital Shortfall Measure of Systemic Risk. *Review of Financial Studies*, *30*(1), 48-79. https://doi.org/10.1093/rfs/hhw060
14. Brunnermeier, M., Gorton, G., Krishnamurthy, A. (2014). Liquidity Mismatch Measurement. In: M. Brunnermeier, A. Krishnamurthy (Eds.), *Risk Topography: Systemic Risk and Macro Modeling*. National Bureau of Economic Research, University of Chicago Press. https://www.nber.org/system/files/chapters/c12514/c12514.pdf
15. Brunnermeier, M.K., Pedersen, L.H. (2009). Market Liquidity and Funding Liquidity. *Review of Financial Studies*, *22*(6), 2201-2238. https://doi.org/10.1093/rfs/hhn098
16. Cao, M., Wei, J. (2005). Stock market returns: A note on temperature anomaly. *Journal of Banking & Finance*, *29*(6), 1559-1573. https://doi.org/10.1016/j.jbankfin.2004.06.028
17. Carney, M. (2015, September 29). Breaking the tragedy of the horizon – climate change and financial stability. *Speech by Mr Mark Carney, Governor of the Bank of England and Chairman of the Financial Stability Board, at Lloyd's of London*. https://www.bis.org/review/r151009a.pdf
18. Chen, N., Jin, X., Xin, B. (2023). The impact of risk spillover network-based multidimensional systemic risks on the real economy. *Applied Economics*, 1-14. https://doi.org/10.1080/00036846.2023.2277689
19. Cont, R., Kotlicki, A., Valderrama, L. (2020). Liquidity at risk: Joint stress testing of solvency and liquidity. *Journal of Banking & Finance*, *118*, 105871. https://doi.org/10.1016/j.jbankfin.2020.105871
20. Dees, S., Henry, J., Martin, R. (Eds.). (2017). *STAMP€: Stress-Test Analytics for Macroprudential Purposes in the euro area*. European Central Bank.
21. Dziwok, E. (2017). Chosen Measures for Pricing of Liquidity. In: K. Jajuga, L.T. Orlowski, K. Staehr (Eds.), *Contemporary Trends and Challenges in Finance* (pp. 3-9). Springer International Publishing.
22. Engle, R. (2018). Systemic Risk 10 Years Later. *Annual Review of Financial Economics*,

10(1), 125-152. https://doi.org/10.1146/annurev-financial-110217-023056

23. ESRB (2021). *Climate-related risk and financial stability, Iss. July*. ECB.
24. ESRB (2022). *The macroprudential challenge of climate change*. https://www.esrb.europa.eu/pub/pdf/reports/esrb.ecb.climate_report202207~622b791878.en.pdf
25. European Central Bank (2010). *Financial Stability Review*. *December*, 147-153.
26. Faccia, D., Parker, M., Stracca, L. (2021). Feeling the heat: extreme temperatures and price stability. *ECB Working Paper Series*, *2626*. https://www.ecb.europa.eu/pub/pdf/scpwps/ecb.wp2626~e86e2be2b4.en.pdf
27. Fama, E.F., French, K.R. (1993). Common risk factors in the returns on stocks and bonds. *Journal of Financial Economics*, *33*(1), 3-56. https://doi.org/10.1016/0304-405X(93)90023-5
28. Foglia, M., Angelini, E. (2021). The triple (<scp>T3</scp>) dimension of systemic risk: Identifying systemically important banks. *International Journal of Finance & Economics*, *26*(1), 7-26. https://doi.org/10.1002/ijfe.2386
29. Freixas, X., Laeven, L., Peydró, J.-L. (2023). *Systemic Risk, Crises, and Macroprudential Regulation*. MIT Press.
30. Giglio, S., Kelly, B., Stroebel, J. (2021). Climate Finance. *Annual Review of Financial Economics*, *13*(1), 15-36. https://doi.org/10.1146/annurev-financial-102620-103311
31. GPW (2017). *Warsaw Stock Exchange Indices*. *October*. https://www.gpw.pl/pub/GPW/files/indeksy/IndicesGPW_1017.pdf
32. Gupta, R., Nel, J., Salisu, A.A., Ji, Q. (2023). Predictability of economic slowdowns in advanced countries over eight centuries: The role of climate risks. *Finance Research Letters*, *54*, 103795. https://doi.org/10.1016/j.frl.2023.103795
33. Hattori, T. (2021). Noise as a liquidity measure: Evidence from the JGB market. *Pacific-Basin Finance Journal*, *67*, 101515. https://doi.org/10.1016/j.pacfin.2021.101515
34. Hepburn, C., O'Callaghan, B., Stern, N., Stiglitz, J., Zenghelis, D. (2020). Will COVID-19 fiscal recovery packages accelerate or retard progress on climate change? *Oxford Review of Economic Policy*, *36*(Supplement_1), S359-S381. https://doi.org/10.1093/oxrep/graa015
35. Hochrainer-Stigler, S., Šakić Trogrlić, R., Reiter, K., Ward, P.J., de Ruiter, M.C., Duncan, M.J., Torresan, S., Ciurean, R., Mysiak, J., Stuparu, D., Gottardo, S. (2023). Toward a framework for systemic multi-hazard and multi-risk assessment and management. *IScience*, *26*(5), 106736. https://doi.org/10.1016/j.isci.2023.106736
36. Hu, G.X., Pan, J., Wang, J. (2013). Noise as Information for Illiquidity. *The Journal of Finance*, *68*(6), 2341-2382. https://doi.org/10.1111/jofi.12083
37. IMF (2009). Global Financial Stability Report (GFSR). Responding to the Financial Crisis and Measuring Systemic Risk. *World Economic and Financial Surveys*, *April*.
38. Jourde, T., Moreau, Q. (2024). Systemic Climate Risk. *SSRN Electronic Journal*. https://doi.org/10.2139/ssrn.4300469

39. Jung, H., Engle, R., Berner, R. (2023). CRISK: Measuring the Climate Risk Exposure of the Financial System. *FRB of New York Staff Report, No. 977*, *March*.
40. Kahn, M.E., Mohaddes, K., Ng, R.N.C., Pesaran, M.H., Raissi, M., Yang, J.-C. (2021). Long-term macroeconomic effects of climate change: A cross-country analysis. *Energy Economics*, *104*, 105624. https://doi.org/10.1016/j.eneco.2021.105624
41. Karydas, C., Xepapadeas, A. (2022). Climate change financial risks: Implications for asset pricing and interest rates. *Journal of Financial Stability*, *63*, 101061. https://doi.org/10.1016/j.jfs.2022.101061
42. Klinke, A., Renn, O. (2002). A New Approach to Risk Evaluation and Management: Risk-Based, Precaution-Based, and Discourse-Based Strategies 1. *Risk Analysis*, *22*(6), 1071-1094. https://doi.org/10.1111/1539-6924.00274
43. Li, C., Liu, Y., Pan, L. (2024). A study of impact of climate change on the U.S. stock market as exemplified by the NASDAQ 100 index constituents. *Scientific Reports*, *14*(1), 15468. https://doi.org/10.1038/s41598-024-66109-7
44. Li, H.-M., Wang, X.-C., Zhao, X.-F., Qi, Y. (2021). Understanding systemic risk induced by climate change. *Advances in Climate Change Research*, *12*(3), 384-394. https://doi.org/10.1016/j.accre.2021.05.006
45. Litterman, B. (2023). *Selling Stranded Assets: Profit, Protection, and Prosperity*. Fact Sheet. Intentional Endowments Network (IEN). https://www.intentionalendowments.org/selling_stranded_assets_profit_protection_and_prosperity
46. Macchiati, V., Brandi, G., Di Matteo, T., Paolotti, D., Caldarelli, G., Cimini, G. (2022). Systemic liquidity contagion in the European interbank market. *Journal of Economic Interaction and Coordination*, *17*(2), 443-474. https://doi.org/10.1007/s11403-021-00338-1
47. Montagna, M., Torri, G., Covi, G. (2020). On the Origin of Systemic Risk. *ECB Working Paper Series, No. 2502*, *December*. https://doi.org/10.2139/ssrn.3749361
48. Morgan, I.G. (1978). Market proxies and the conditional prediction of returns. *Journal of Financial Economics*, *6*(4), 385-398. https://doi.org/10.1016/0304-405X(78)90011-9
49. Nelson, C., Siegel, A.F. (1987). Parsimonious Modeling of Yield Curves. *The Journal of Business*, *60*(4), 473-489. https://econpapers.repec.org/RePEc:ucp:jnlbus:v:60:y:1987:i:4:p:473-89
50. Nguyen, Q., Diaz-Rainey, I., Kuruppuarachchi, D. (2023). In search of climate distress risk. *International Review of Financial Analysis*, *85*, 102444. https://doi.org/10.1016/j.irfa.2022.102444
51. Pagnottoni, P., Spelta, A., Flori, A., Pammolli, F. (2022). Climate change and financial stability: Natural disaster impacts on global stock markets. *Physica A: Statistical Mechanics and Its Applications*, *599*, 127514. https://doi.org/10.1016/j.physa.2022.127514
52. Reboredo, J.C., Ugolini, A. (2022). Climate transition risk, profitability and stock prices. *International Review of Financial Analysis*, *83*, 102271. https://doi.org/10.1016/j.irfa.2022.102271

53. Renn, O., Klinke, A., Schweizer, P.-J. (2018). Risk Governance: Application to Urban Challenges. *International Journal of Disaster Risk Science*, *9*(4), 434-444. https://doi.org/10.1007/s13753-018-0196-3
54. Rochet, J.-C., Tirole, J. (1996). Interbank Lending and Systemic Risk. *Journal of Money, Credit and Banking*, *28*(4), 733. https://doi.org/10.2307/2077918
55. Semieniuk, G., Holden, P.B., Mercure, J.-F., Salas, P., Pollitt, H., Jobson, K., Vercoulen, P., Chewpreecha, U., Edwards, N.R., Viñuales, J.E. (2022). Stranded fossil-fuel assets translate to major losses for investors in advanced economies. *Nature Climate Change*, *12*(6), 532-538. https://doi.org/10.1038/s41558-022-01356-y
56. Sharpe, W.F. (1964). Capital Asset Prices: A Theory of Market Equilibrium Under Conditions of Risk. *The Journal of Finance*, *19*(3), 425-442. https://doi.org/10.1111/j.1540-6261.1964.tb02865.x
57. Smaga, P. (2014). The Concept of Systemic Risk. *Systemic Risk Centre Special Paper, Vol. 5*. https://eprints.lse.ac.uk/61214/1/sp-5.pdf
58. Svensson, L.E.O. (1994). Estimating and Interpreting Forward Interest Rates: Sweden 1992-1994. *IMF Working Papers*, *94*(114), 1. https://doi.org/10.5089/9781451853759.001
59. Tsai, S.-C. (2012). Liquidity and Yield Curve Estimation. *Emerging Markets Finance and Trade*, *48*(5), 4-24. https://doi.org/10.2753/REE1540-496X480501
60. Undheim, T.A. (2024). An interdisciplinary review of systemic risk factors leading up to existential risks. *Progress in Disaster Science*, *22*, 100326. https://doi.org/10.1016/j.pdisas.2024.100326
61. van der Ploeg, F., Rezai, A. (2020). Stranded Assets in the Transition to a Carbon-Free Economy. *Annual Review of Resource Economics*, *12*(1), 281-298. https://doi.org/10.1146/annurev-resource-110519-040938
62. Wu, X., Bai, X., Qi, H., Lu, L., Yang, M., Taghizadeh-Hesary, F. (2023). The impact of climate change on banking systemic risk. *Economic Analysis and Policy*, *78*, 419-437. https://doi.org/10.1016/j.eap.2023.03.012