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# Systemic risk and climate change: a joint impact of transition and physical climate risks on the Polish banking sector

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## Abstract

This study examines how climate change affects systemic risk in the Polish banking sector, focusing on both physical and transition climate risks. We argue that jointly integrating these risks provides a more accurate view of systemic vulnerability. Using a multidimensional framework, we extend the climate stability measure CRISK by incorporating temperature anomalies (physical risk) and a stranded assets index (transition risk). The dataset spans 2005–2023 and covers stock prices of eight systemically important banks, market shocks, and climate proxies tailored to the Polish context. Bank-specific sensitivity factors are estimated with a multivariate GJR-DCC-GARCH model on monthly data, capturing time-varying relationships between market and climate factors. The results show climate shocks significantly increase systemic risk, especially during crises such as Covid-19 and the war in Ukraine, with banks exposed to brown assets most fragile. The study is the first to jointly integrate both climate risks in Poland, offering a replicable methodology for other contexts.

**Keywords:** climate risk, systemic risk, financial stability, transition risk, physical risk

**JEL:** G20, Q54, C53

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## 1. Introduction

Climate change has become a defining challenge in the discourse on systemic risk, introducing novel uncertainties for financial stability. These risks are multifaceted, including physical risks, such as extreme weather events and environmental degradation, and transition risks, related to economic and regulatory shifts toward a low-carbon economy. Both dimensions can significantly affect financial systems, as emphasized by Carney (2015), who highlights the importance of integrating climate risks into systemic risk frameworks. The urgency of this task has been further amplified by recent global crises, including the Covid-19 pandemic (Hepburn et al. 2020) and ongoing geopolitical tensions (Jourde, Moreau 2024; Jung, Engle, Berner 2025), which underscore the need for incorporating climate risk into systemic risk assessment.

Despite growing recognition of climate-related threats, existing research often examines physical and transition risks in isolation. However, these risks are interdependent and can amplify one another, exacerbating systemic vulnerabilities. Capturing these interconnections is crucial for creating a comprehensive systemic risk framework.

We hypothesize that integrating transition and physical climate risks improve systemic risk assessment, and that this joint measure can identify periods of heightened vulnerability for systemically important banks.

To test this hypothesis, we extend the climate systemic risk measure (CRISK) proposed by Jung, Engle, and Berner (2023; 2025) by incorporating an additional physical risk dimension. Our joint measure, developed using the Systemic Expected Shortfall (SES) methodology of Acharya et al. (2017), aligns with Basel Committee on Banking Supervision recommendations for integrating climate risks into conventional financial risk frameworks (BCBS 2021). Unlike prior studies that rely on global indices, we construct local proxies tailored to the Polish market: temperature anomalies to capture physical risk and a stranded assets index for transition risk.

We estimate the bank-specific sensitivity factors to market and climate shocks using a multivariate GJR-DCC-GARCH model, which captures time-varying relationships and enables us to construct a joint transition-physical climate systemic risk measure. This approach allows us to evaluate both the isolated and joint impacts of climate and market shocks on systemic vulnerability.

The objective of this paper is to assess the stability risks of the Polish financial system, focusing on eight systemically important banking institutions from January 2005 to December 2023. By incorporating both transition and physical climate risks, our study provides practical insights into regional financial stability and contributes to the broader discussion on climate-related systemic risks by offering a replicable, market-based framework that can be applied to other regions.

The remainder of the paper proceeds as follows: Section 2 provides a literature review on the interconnection between climate change and financial stability. Section 3 describes the methodology of our extended model, detailing the assessment of market, transition, and physical climate shocks and their integration into a systemic risk measure. Section 4 presents the data and local proxies used. Section 5 presents the empirical results, including beta estimation, the joint transition and physical climate systemic risk measure, risk measures in isolation, and a decomposition of the joint climate risk measure. Finally, Section 6 concludes with a discussion of the findings and their implications.

## 2. Climate systemic risk literature review

Systemic risk associated with climate change has become a focal point of financial stability research, driven by its potential to destabilize economies through interdependent and cascading impacts. Early frameworks, such as the Bank of England's classification of physical risks and transition risks (Batten, Sowerbutts, Tanaka 2016; BCBS 2021), significantly influence subsequent studies and policy initiatives. Physical risks refer to the immediate disruptions caused by extreme weather events like floods, hurricanes, and droughts, which negatively impact businesses, financial institutions, and markets. Conversely, transition risks are linked to the regulatory and economic adjustments required to shift toward a low-carbon economy, often manifesting in declining asset values for carbon-intensive industries (Zhang, Zhang, Lu 2022).

The concept of systemic risk itself has evolved over time, expanding from its initial association with the collapse of major financial institutions to encompass broader interdependencies and contagion effects across markets (Montagna, Torri, Covi 2020; Freixas, Laeven, Peydró 2023; Undheim 2024). The global financial crisis of 2007–2009 was a watershed moment, leading to calls for more comprehensive systemic risk analyses that account for both endogenous and exogenous shocks (IMF 2009; ECB 2010). The modelling of systemic risk and its drivers increasingly relies on multivariate GARCH--type models which allow for the construction of a time-varying conditional variance-covariance matrix of financial returns or risk factors. Early work, such as Bollerslev, Engle, and Wooldridge (1988), introduce the MGARCH concept, followed by more tractable specifications such as the BEKK model (Engle, Kroner 1995) and the Dynamic Conditional Correlation (DCC) model (Engle 2002). While BEKK-type specifications offer a flexible framework for modelling cross-dynamics between variances, they are computationally demanding and prone to overparametrisation, even when applied to a small amount of series. In contrast, the DCC specification provides a parsimonious but effective approach to capture time-varying correlations while maintaining the univariate GARCH dynamics in conditional variances. For this reason, DCC-GARCH has become a widely used tool in systemic risk applications (Brownlees, Engle 2017; Engle, Jondeau, Rockinger 2015).

Climate risks represent a new frontier in this discourse, challenging existing frameworks with their multidimensional and uncertain nature (BCBS 2021; ESRB 2021, 2022). Central banks and regulatory institutions have increasingly recognized these risks, with initiatives like the Network for Greening the Financial System (NGFS) emphasizing climate stress tests to bolster financial stability (NGFS 2019, 2021). Policymakers, including the European Central Bank (ECB), Bank of Japan (BoJ), and the Federal Reserve System (FRS), have developed strategies to manage climate-related financial risks, ranging from scenario analyses to comprehensive policy frameworks (Alogoskoufis et al. 2021; Kuroda 2021; FRS 2023).

Climate risks challenge existing analytical frameworks and require innovative approaches to comprehensively assess their impact. Perspectives on systemic risk vary significantly, with regulators often prioritizing macroeconomic disruptions, while market participants focus on asset price volatility (Benoit et al. 2017; Giglio, Kelly, Stroebel 2021; Nguyen, Diaz-Rainey, Kuruppuarachchi 2023).

Academic literature mirrors these efforts, seeking to classify, measure, and model climate-related risks. A dominant trend is to analyse physical and transition risks independently, as in Faccini, Matin, and Skiadopoulos (2023), who use textual analysis of climate-change news to assess transition risks, and Del Fava et al. (2024), who apply machine-learning techniques to evaluate physical risk spillovers across countries.

However, the interdependence of risks poses challenges to fragmented approaches, highlighting the necessity of a more integrated framework to capture their systemic implications. Renn, Klinke, and Schweizer (2018) and Li, Liu, and Pan (2024) explore the cascading nature of systemic risks, while Hoffart et al. (2024) identify four interconnected dimensions: climate crisis, financial (in)stability, geopolitical energy crises, and energy transition. Foglia and Angelini (2021) propose a new systemic risk measure based on a multi-way analysis (time and the cross-dimension), while Chen, Jin, and Xin (2023) use multidimensional systemic risk measures based on dynamic risk spillover networks to quantify the level, transmission speed, and transmission breadth.

An integrated perspective is emerging as researchers attempt to develop consolidated measures of climate-related systemic risk. Curcio, Gianfrancesco, and Vioto (2023) employ ΔCoVaR and MES methodologies to assess the systemic risk of US banks and insurers while comparing green and brown companies' resilience to physical and transition risks. This holistic approach aligns with the broader trend of applying market-based metrics to quantify interconnected financial risks, as advocated by Cai et al. (2018). Albanese et al. (2024) investigate the effects of physical and transition risks on stock markets, while Borsuk et al. (2025) analyse the impact on credit ratings. Birindelli et al. (2024) highlight the critical role of climate risk as a driver of financial stability.

To address these gaps, we adopt a comprehensive approach to systemic risk analysis, considering both climate-related risks alongside market factors. Extending the methodology developed by Jung, Engle, and Berner (2023, 2025), we highlight the growing importance of climate risk as an underestimated but increasingly influential dimension of systemic risk.

## 3. Climate systemic risk measurement methodology

In this study we adopt a methodology based on the systemic risk measure SRISK (Brownlees, Engle 2017; Engle 2018) and extend the two-dimensional CRISK framework of Jung, Engle, and Berner (2023, 2025), which captures market and transition climate risks, into a three-dimensional setting by incorporating physical climate risk. In doing so, we incorporate not only transition-related shocks, but also risks arising from the direct effects of climate change, such as temperature anomalies. We build this extension on the concept of Systemic Expected Shortfall (SES) proposed by Acharya et al. (2017), and our approach is consistent with related methodologies, such as ΔCoVaR (Adrian, Brunnermeier 2016). We choose the SRISK model because it allows us to measure the sensitivity of financial institutions to external shocks and has proven effective in capturing non-market risks, including those related to climate change.

### 3.1. Systemic risk measure

In this context, we define the 'system' specifically as the banking system, defined as the weighted aggregation of systemically important financial institutions identified by the European Banking Authority (Benoit et al. 2017). Using this framework, we analyse the vulnerability of the banking system to individual shocks, both at the institutional level and as a composite measure for the broader system.

The system's rate of return at time $t$, denoted by $r_{s,t}$ is calculated as a weighted sum of the individual rates of return of the $N$ systemically important institutions:

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

where $w_{i,t}$ represents the weight of the $i$-th institution within the system at time $t$ determined by metrics such as market capitalisation or systemic importance scores (e.g. SIFI or O-SII scores). Meanwhile, $r_{i,t}$ is the stock return rate of the $i$-th institution, $i = 1,..., N$.

The methodology relies on publicly available market data and centres on the concept of capital shortfall of the $i$-th institution $CS_{i,t}$ as introduced by Brownlees and Engle (2017). On any given day $t$, the capital shortfall is expressed as:

$$CS_{i,t} = \overbrace{k\left(D_{i,t} + V_{i,t}\right)}^{\text{capital reserves}} - \overbrace{V_{i,t}}^{\text{current equity}} \tag{2}$$

where $D_{i,t}$ represents the book value of debt of the $i$-th institution, $V_{i,t}$ is the market value of equity of the $i$-th institution, and $k$ is the prudential capital fraction. A negative capital shortfall indicates surplus capital, whereas a positive value signifies a deficit.

The SRISK metric estimates the capital shortfall that the $i$-th institution may face in the event of a shock over a specified time horizon $h$:

$$SRISK_{i,t} = \mathrm{E}\left(CS_{i,t+h} \mid \text{systemic event}\right) \tag{3}$$

Following definitions by the ECB (2010) and Acharya et al. (2017), a systemic event is described as financial instability severe enough to disrupt the financial intermediation process, thereby impairing economic growth and societal welfare. For the system $SRISK_{s,t} = \sum_{i=1}^{N} SRISK_{i,t}$.

Formally, a systemic event occurs when the rate of return or rate of change of the risk factor $r_t^{rf}$, crosses a critical threshold $\theta^{rf}$. The direction of the threshold depends on the nature of the factor: for market and transition risk, shocks are typically associated with large negative returns (lower-tail events), while for physical risk, systemic shocks correspond to extreme increases in temperature anomalies (upper-tail events). Alternatively, $\theta^{rf}$ may be defined as a chosen percentile of the historical distribution of the risk factor (VaR).

An expected shortfall (ES) for the system is a short-run expected equity return conditional on the risk factor exceeding the threshold $\theta^{rf}$ at time $t$. For systemic events that are triggered by lower-tail realizations:

$$ES_{s,t} = \mathrm{E}\left(r_{s,t} \mid r_t^{rf} < \theta^{rf}\right) = \sum_{i=1}^{N} w_{i,t} \cdot \mathrm{E}\left(r_{i,t} \mid r_t^{rf} < \theta^{rf}\right) \tag{4a}$$

Here $\theta^{rf}$ is defined as $VaR_t^{rf,q} = F_q^{-1}\left(r_{t-h,t}^{rf}\right)$, where $q$ represents an arbitrarily chosen quantile of the distribution, and $r_{t-h,t}^{rf}$ denotes the historical return of a risk factor proxy.

Following Acharya, Engle, and Richardson (2012), and Acharya et al. (2017), the Marginal Expected Shortfall (MES) of the *i*-th institution is the partial derivative of the system ES with respect to the institution's weight:

$$MES_{i,t} = \frac{\partial ES_{s,t}}{\partial w_{i,t}} = \mathrm{E}\left(r_{i,t} \mid r_t^{rf} < \theta^{rf}\right) \tag{4b}$$

The Long-Run Marginal Expected Shortfall (LRMES) is the conditional expectation of the *i*-th institution's multi-period equity return over a defined horizon *h*, under the assumption that a systemic event will occur. For the lower-tail events we write:

$$LRMES_{i,t} = -\mathrm{E}\left(r_{i,t+h} \mid r_{t+h}^{rf} < \theta^{rf}\right) \tag{4c}$$

To capture the physical climate shocks that occur in the upper tail of the factor distribution, we modify formulas (4a–4c) as follows:

$$ES_{s,t} = \mathrm{E}\left(r_{s,t} \mid r_t^{rf} > \theta^{rf}\right) = \sum_{i=1}^{N} w_{i,t} \cdot \mathrm{E}\left(r_{i,t} \mid r_t^{rf} > \theta^{rf}\right) \tag{5a}$$

$$MES_{i,t} = \frac{\partial ES_{s,t}}{\partial w_{i,t}} = \mathrm{E}\left(r_{i,t} \mid r_t^{rf} > \theta^{rf}\right) \tag{5b}$$

$$LRMES_{i,t} = -\mathrm{E}\left(r_{i,t+h} \mid r_{t+h}^{rf} > \theta^{rf}\right) \tag{5c}$$

The LRMES is a normalized measure, expressed as the expected percentage loss in equity value over horizon *h* conditional on the systemic event. By construction, it takes positive values whenever the conditional expectation of returns is negative, reflecting the anticipated proportional decline in equity. As a random variable, $LRMES_{i,t}$ requires estimation through specialized statistical methodology, which is elaborated upon later in this study.

Systemic risk, as outlined in formula (3), represents the expected capital shortfall of the *i*-th institution in the event of a shock. It can be expressed using LRMES as follows:

$$SRISK_{i,t} = \overbrace{k\left(D_{i,t} + \left(1 - LRMES_{i,t}\right)V_{i,t}\right)}^{\text{required capital}} - \overbrace{\left(1 - LRMES_{i,t}\right)V_{i,t}}^{\text{current capital}} \tag{6}$$

Under extreme stress conditions, where $LRMES_{i,t} \to 1$, the *i*-th institution's market capitalisation is effectively reduced to zero, and $SRISK_{i,t}$ quantifies the associated capital shortfall over the selected horizon. In this context, $SRISK_{i,t}$ represents a forward-looking measure of the capital reserves necessary to absorb shocks during a financial crisis. It depends on the *i*-th institution's overall scale, leverage ratios, and risk characteristics.

In practice, managers are primarily concerned with addressing capital shortfalls rather than surplus levels. Consequently, SRISK is defined as:

$$SRISK_{i,t} = \max\left\{0;\ kD_{i,t} - (1-k)\left(1 - LRMES_{i,t}\right)V_{i,t}\right\} \tag{7}$$

To compute SRISK, an external shock is characterized by a significant market downturn, represented by the market stock index return $r_{m,t} < \theta^M$. Studies indicate that comprehensive stock market indices, such as the S&P 500 or MSCI World, serve as effective proxies for capturing overall market trends and maintain a strong correlation with broader economic activity (Morgan 1978; Bali, Engle, Murray 2017). For studies focusing on local markets, the general index of the relevant local stock exchange is typically used.

Following the methodology of Brownlees and Engle (2017) and the V-Lab procedure, we estimate the Long-Run Marginal Expected Shortfall (LRMES) using the GJR-DCC-GARCH model as follows:

$$LRMES_{i,t}^{M} = 1 - \exp\left(\beta_{i,t}^{M} \cdot \log\left(1 - \theta^{M}\right)\right) \tag{8}$$

where $\beta_{i,t}^{M}$ expresses the sensitivity of the *i*-th institution to the market shock estimated for the threshold $\theta^M \equiv VaR_t^{M,q}$ with *q* denoting the chosen quantile of the distribution.

To build the model for estimating the sensitivity factor $\beta_{i,t}^{M}$ we first propose that, given the information set available at time *t* – 1, the vector of log returns can be described using a multivariate volatility representation:

$$\mathbf{r_{i,t}} = \begin{bmatrix} r_{i,t} \\ r_{m,t} \end{bmatrix} = \begin{bmatrix} \sigma_{i,t}\,\varepsilon_{i,t} \\ \sigma_{m,t}\,\varepsilon_{m,t} \end{bmatrix} = \begin{bmatrix} \sigma_{i,t} & 0 \\ 0 & \sigma_{m,t} \end{bmatrix} \begin{bmatrix} \varepsilon_{i,t} \\ \varepsilon_{m,t} \end{bmatrix} = \mathbf{H}_{\mathbf{i,t}}^{1/2} \cdot \boldsymbol{\varepsilon}_{\mathbf{i,t}} \tag{9}$$

where $\mathbf{r_{i,t}}$ represents the vector of returns at time *t*, and $\boldsymbol{\varepsilon}_{\mathbf{i,t}}$ is an i.i.d. vector with $\mathrm{E}(\boldsymbol{\varepsilon}_{\mathbf{i,t}}) = 0$ and $\mathrm{E}\left(\boldsymbol{\varepsilon}_{\mathbf{i,t}}\boldsymbol{\varepsilon}_{\mathbf{i,t}}^{'}\right)$ being a two-by-two identity matrix.

The covariance matrix $\mathbf{H_{i,t}}$ is then:

$$\mathbf{H}_{\mathbf{i,t}} = \mathrm{Var}\left(\mathbf{r}_{\mathbf{i,t}}\right) = \begin{bmatrix} \sigma_{i,t}^{2} & \sigma_{i,t}\,\sigma_{m,t}\,\rho_{i,m,t} \\ \sigma_{i,t}\,\sigma_{m,t}\,\rho_{i,m,t} & \sigma_{m,t}^{2} \end{bmatrix} \tag{10}$$

where $\sigma_{m,t}$ and $\sigma_{i,t}$ are the conditional standard deviation for the market and the financial institution *i* at time *t*, respectively, while $\rho_{i,m,t}$ is the time-varying conditional correlation coefficient.

Therefore, the time-varying beta captures an asset's dynamic exposure to systematic market risk, reflecting shifts in correlation and relative volatility that characterize stability risk over time:

$$\beta_{i,t}^{M} \equiv \frac{\mathrm{Cov}\left(r_{i,t},\ r_{m,t}\right)}{\mathrm{Var}\left(r_{m,t}\right)} = \frac{\sigma_{i,t}\,\sigma_{m,t}\,\rho_{i,m,t}}{\sigma_{m,t}^{2}} = \frac{\sigma_{i,t}}{\sigma_{m,t}}\rho_{i,m,t} \tag{11}$$

Because all values in (11) are time-varying, the GJR-DCC GARCH framework is used. First, the conditional volatilities of individual series are modelled with GJR-GARCH (Glosten, Jagannathan, Runkle 1993; Engle 2002), then the dynamic correlation structure across series (between each institution *i* and the market index) is estimated using the DCC-GARCH model (Engle 2002, 2009).

In the first step, we estimate the return volatility dynamics using the GJR-GARCH specification, which can be expressed as follows:

$$\sigma_{i,t}^2 = \omega_{Vi} + \alpha_{Vi} r_{i,t-1}^2 + \gamma_{Vi} r_{i,t-1}^2 I_{i,t-1}^- + \beta_{Vi} \sigma_{i,t-1}^2 \tag{12a}$$

$$\sigma_{m,t}^2 = \omega_{Vm} + \alpha_{Vm} r_{m,t-1}^2 + \gamma_{Vm} r_{m,t-1}^2 I_{m,t-1}^- + \beta_{Vm} \sigma_{m,t-1}^2 \tag{12b}$$

where $I_{i,t-1}^-$, $I_{m,t-1}^-$ are indicator functions equal to 1 if $r_{i,t} < 0$ and $r_{m,t} < 0$ respectively and 0 otherwise.

In the second step we estimate the dependence structure across series with the standard DCC-GARCH model based on the volatility-adjusted returns from equation (9): $\varepsilon_{i,t} = r_{i,t} / \sigma_{i,t}$, $\varepsilon_{m,t} = r_{m,t} / \sigma_{m,t}$. The time-varying correlation structure is described as follows:

$$\mathrm{Cor}\begin{pmatrix} \varepsilon_{i,t} \\ \varepsilon_{m,t} \end{pmatrix} = \begin{bmatrix} 1 & \rho_{i,m,t} \\ \rho_{i,m,t} & 1 \end{bmatrix} = \mathrm{diag}\left(Q_{i,m,t}\right)^{-1/2} Q_{i,m,t}\, \mathrm{diag}\left(Q_{i,m,t}\right)^{-1/2} \tag{13}$$

The DCC model specifies the dynamics of the pseudo-correlation matrix $Q_{i,m,t}$ as:

$$Q_{i,m,t} = \left(1 - \alpha_{Ci} - \beta_{Ci}\right) S_i + \alpha_{Ci} \begin{bmatrix} \varepsilon_{i,t} \\ \varepsilon_{m,t} \end{bmatrix} \begin{bmatrix} \varepsilon_{i,t} \\ \varepsilon_{m,t} \end{bmatrix}' + \beta_{Ci} Q_{i,m,t-1} \tag{14}$$

where $S_i$ is the unconditional correlation of adjusted returns.

Therefore, the time-varying beta captures an asset's dynamic exposure to systematic market risk, reflecting shifts in correlation and relative volatility that characterize stability risk over time.

## 3.2. Climate systemic risk measure

Jung, Engle, and Berner (2025) and V-Lab develop a framework for evaluating the combined sensitivity of the financial system to market and climate transition risk. This framework, often referred to as climate-SRISK (CRISK), provides a formal attempt to link systemic financial vulnerability with climate--related factors. The model is defined as follows:[1]

$$S \mid TrCRISK_{i,t} = kD_{i,t} - \left(1-k\right) V_{i,t} \left(1 - LRMES_{i,t}^{M}\right)\left(1 - LRMES_{i,t}^{Tr}\right) \tag{15}$$

[1] To be consistent with Jung, Engle, and Berner (2023, 2025), we assume that the threshold is represented by a positive number $-\theta$ (Jung et al. 2023, p. 70), which affects the sign of $\theta$ in the LRMES formula. This specification is particularly important when the analysis includes both lower and upper-tail events.

where:

$$LRMES_{i,t}^{M} = 1 - \exp\left(\beta_{i,t}^{M} \cdot \log\left(1-\theta^{M}\right)\right)$$

$$LRMES_{i,t}^{Tr} = 1 - \exp\left(\beta_{i,t}^{Tr} \cdot \log\left(1-\theta^{Tr}\right)\right)$$

Equation (15) captures the interdependence between market and transition climate shocks. Here, $\beta_{i,t}^{M}$ denotes the sensitivity of institution $i$ to market shocks in the presence of transition climate shocks, while $\beta_{i,t}^{Tr}$ represents the sensitivity to transition climate shocks in the presence of market shocks. Both coefficients are estimated jointly using the same GJR-DCC-GARCH procedure, extended to an additional dimension.

To incorporate the transition-related factor in practice, appropriate proxies must be defined. Following the approach of Jung, Engle, and Berner (2023, 2025), a proxy for transition climate risk is constructed using a portfolio of stranded assets, with a focus on industries such as oil, fossil fuels, and coal. These sectors are particularly vulnerable to transition risk, as climate policies like the Paris Agreement are expected to reduce demand for their products. This anticipated decline in demand significantly threatens their long-term profitability as the global economy moves toward carbon neutrality (van der Ploeg, Rezai 2020; Bolton, Kacperczyk 2021). The stranded asset portfolio mentioned by Jung, Engle, and Berner (2023; 2025), originally developed by Litterman in collaboration with 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 (WWF Stranded Asset Swap). Since KOL was delisted in 2021, its returns have been replaced by the average returns of its five largest holdings. This portfolio generates positive returns when either XLE or KOL outperforms the market, and negative returns otherwise, effectively reflecting elevated transition risk. Alternative proxies for transition climate risk can also be constructed using assets tied to the coal, oil, and gas sectors (commonly referred to as 'brown industry' indices). Such proxies typically involve a long position in ETFs or indices representing these sectors and a short position in a broad market index (Reboredo, Ugolini 2022; Semieniuk et al. 2022). This approach allows for flexible adaptation to various market conditions while maintaining sensitivity to transition-related risks.

The CRISK model developed by Jung, Engle, and Berner (2023, 2025) relies solely on proxies for transition risk, ignoring the impact of physical climate shocks. However, growing research highlights the importance of incorporating physical climate risk into systemic risk assessments. To approximate physical climate risk, external shocks are often defined as deviations from long-term average temperatures (typically over a 30-year reference period), referred to as term temperature anomalies. This method assumes that abnormal temperature changes can disrupt economic activity, particularly in climate-dependent industries, as is noted by Faccia, Parker, and Stracca (2021), Kahn et al. (2021), and Karydas and Xepapadeas (2022). Furthermore, theoretical models demonstrate a connection between temperature anomalies and stock market fluctuations (Gupta et al. 2023), with evidence indicating that the magnitude of this effect has grown in recent years (Li, Liu, Pan 2024). Studies by Faccia, Parker, and Stracca (2021), Pagnottoni et al. (2022), Acharya et al. (2023), and Wu et al. (2023) also show that temperature deviations heighten financial risks and destabilize banks, particularly those with significant exposure to climate-sensitive sectors. While temperature anomalies are most commonly employed in identifying physical climate risks, other meteorological factors – such as precipitation, humidity, rainfall, wind speed, and cloud cover – also play a critical role in providing a comprehensive understanding of climate disruptions and in managing their financial impacts.

### 3.3. Systemic transition climate and physical climate joint risk measure

Although the existing CRISK framework captures transition-related exposures, it does not account for risks arising from physical climate shocks. To address this limitation, we extend and refine the methodology by adding physical climate risk as an additional dimension and introduce a three-factor model (Dziwok, Szczepaniak 2025). In our approach, physical climate shocks are approximated by deviations from long-term average temperatures, commonly referred to as temperature anomalies.

The joint transition and physical climate systemic risk measure, denoted as $S\left|Tr\right|PhCRISK_{i,t}$, captures common effects of market stress and climate-related stresses, and is defined as:

$$S\left|Tr\right|PhCRISK_{i,t} = kD_{i,t} - \left(1-k\right)V_{i,t}\left(1-LRMES_{i,t}^{M}\right)\left(1-LRMES_{i,t}^{Tr}\right)\left(1-LRMES_{i,t}^{Ph}\right) \tag{16}$$

Here, $LRMES_{i,t}^{M} = 1-\exp\left(\beta_{i,t}^{M}\cdot\log\left(1-\theta^{M}\right)\right)$ represents the conditional expectation under market stress, capturing the interdependence between market and both transition and physical climate risk, thus extending the measure by one dimension compared to equation (15). $\beta_{i,t}^{M}$ is the sensitivity factor of the institution *i* to market shocks with the existence of both types of climate shocks. Similarly, $LRMES_{i,t}^{Tr} = 1-\exp\left(\beta_{i,t}^{Tr}\cdot\log\left(1-\theta^{Tr}\right)\right)$ is the conditional expectation of a bank's multi-period return on equity under the climate transition stress scenario with $\beta_{i,t}^{Tr}$ being the risk factor associated with climate transition shocks.

$LRMES_{i,t}^{Ph}$ is the conditional expectation of the *i*-th institution's multi-period return on equity under the physical climate stress scenario:

$$LRMES_{i,t}^{Ph} = 1-\exp\left(\beta_{i,t}^{Ph}\cdot\log\left(1+\theta^{Ph}\right)\right) \tag{17}$$

where $\beta_{i,t}^{Ph}$ represents the risk factor associated with physical climate shocks.

The methodology expressed in (16) is sufficiently universal to integrate additional fragility measures for both external and internal stress scenarios.

Given the interdependence between climate and market factors, external risks cannot be fully isolated from market risks. For exogenous risks beyond market factors, an approach similar to the Fama--French factor model (Fama, French 1993) is applied. This method incorporates the mutual dependence between the analysed climate risks and market factors, as discussed in Dziwok and Szczepaniak (2024).

We extend the dynamic conditional beta (DCB) model developed by Engle to estimate beta coefficients. This approach leverages a multivariate GARCH framework with dynamic conditional correlations (GJR-DCC-GARCH) to capture the time-varying nature of sensitivities. In this model, the transposed return vector at time *t*, is represented as $\mathbf{r}_{\mathbf{i,t}}^{'} = \left[r_{i,t}, r_{m,t}, r_{tr,t}, r_{ph,t}\right]$, and the corresponding i.i.d. vector is given by $\boldsymbol{\varepsilon}_{\mathbf{i,t}}^{'} = \left[\varepsilon_{i,t}, \varepsilon_{m,t}, \varepsilon_{tr,t}, \varepsilon_{ph,t}\right]$ where $\mathrm{E}\left(\boldsymbol{\varepsilon}_{\mathbf{i,t}}\right) = 0$ and $\mathrm{E}\left(\boldsymbol{\varepsilon}_{\mathbf{i,t}}\boldsymbol{\varepsilon}_{\mathbf{i,t}}^{'}\right)$ forms a four-by-four identity matrix.

The covariance matrix $\mathbf{H}_{\mathbf{i,t}}$ at time *t*, is expressed as:

$$\mathbf{H}_{\mathbf{i,t}} = \begin{bmatrix} \sigma_{i,t}^{2} & \sigma_{i,t}\sigma_{m,t}\rho_{i,m,t} & \sigma_{i,t}\sigma_{tr,t}\rho_{i,tr,t} & \sigma_{i,t}\sigma_{ph,t}\rho_{i,ph,t} \\ \sigma_{i,t}\sigma_{m,t}\rho_{i,m,t} & \sigma_{m,t}^{2} & \sigma_{m,t}\sigma_{tr,t}\rho_{m,tr,t} & \sigma_{m,t}\sigma_{ph,t}\rho_{m,ph,t} \\ \sigma_{i,t}\sigma_{tr,t}\rho_{i,tr,t} & \sigma_{m,t}\sigma_{tr,t}\rho_{m,tr,t} & \sigma_{tr,t}^{2} & \sigma_{tr,t}\sigma_{ph,t}\rho_{tr,ph,t} \\ \sigma_{i,t}\sigma_{ph,t}\rho_{i,ph,t} & \sigma_{m,t}\sigma_{ph,t}\rho_{m,ph,t} & \sigma_{tr,t}\sigma_{ph,t}\rho_{tr,ph,t} & \sigma_{ph,t}^{2} \end{bmatrix} \tag{18}$$

where $\sigma_{i,t}, \sigma_{m,t}, \sigma_{tr,t}, \sigma_{ph,t}$ denote the conditional standard deviations of the respective proxies, while $\rho_{i,j,t}$ are the time-varying conditional correlations.

By extending from bivariate to multivariate process, the modelling framework introduces additional challenges, particularly in accounting for dynamic correlations. These time-varying correlations enable a more nuanced and adaptive representation of risk dependencies, critical for accurately evaluating systemic risk. Ignoring these, variations can significantly underestimate systemic vulnerabilities, with adverse implications for risk management.

The beta coefficients for market risk ($\beta_{i,t}^{M}$), transition climate risk ($\beta_{i,t}^{Tr}$) and physical climate risk ($\beta_{i,t}^{Ph}$) are derived as follows:

$$\begin{bmatrix} \beta_{i,t}^{M} \\ \beta_{i,t}^{Tr} \\ \beta_{i,t}^{Ph} \end{bmatrix} = \begin{bmatrix} \sigma_{m,t}^{2} & \sigma_{m,t}\,\sigma_{tr,t}\,\rho_{m,tr,t} & \sigma_{m,t}\,\sigma_{ph,t}\,\rho_{m,ph,t} \\ \sigma_{m,t}\,\sigma_{tr,t}\,\rho_{m,tr,t} & \sigma_{tr,t}^{2} & \sigma_{tr,t}\,\sigma_{ph,t}\,\rho_{tr,ph,t} \\ \sigma_{m,t}\,\sigma_{ph,t}\,\rho_{m,ph,t} & \sigma_{tr,t}\,\sigma_{ph,t}\,\rho_{tr,ph,t} & \sigma_{ph,t}^{2} \end{bmatrix}^{-1} \begin{bmatrix} \sigma_{i,t}\,\sigma_{m,t}\,\rho_{i,m,t} \\ \sigma_{i,t}\,\sigma_{tr,t}\,\rho_{i,tr,t} \\ \sigma_{i,t}\,\sigma_{ph,t}\,\rho_{i,ph,t} \end{bmatrix} \tag{19}$$

We employ the DCB model to estimate time-varying betas, while the GJR-DCC-GARCH model captures fluctuations in both variability and correlation over time.

To calculate the isolated effect of climate factors, we assume in (16) the absence of market shock ($LRMES_{i,t}^{M} = 0$). This approach allows us to quantify the total capital required to address stress caused exclusively by both transition climate and physical climate risks, considering an existing capital base of financial institutions. The isolated transition and physical climate risk measure is as follows:

$$Tr \mid PhCRISK_{i,t} = kD_{i,t} - \left(1-k\right)V_{i,t}\left(1-LRMES_{i,t}^{Tr}\right)\left(1-LRMES_{i,t}^{Ph}\right) \tag{20}$$

To achieve an isolated systemic risk of the *i*-th institution (in the absence of transmission and climate shock), we assume $LRMES_{i,t}^{Tr} = LRMES_{i,t}^{Ph} = 0$ and is simplifying to the case similar to (7) but with $\beta_{i,t}^{M}$ derived from (16):

$$SRISK_{i,t} = kD_{i,t} - \left(1-k\right)V_{i,t} \cdot \exp\left(\beta_{i,t}^{M} \cdot \log\left(1-\theta^{M}\right)\right) \tag{21}$$

The SRISK measure in equation (7) is not identical to the SRISK measure in equation (21), as the market beta in the latter is estimated within a three-dimensional model that incorporates not only the market component, but also transition and physical climate risk factors. By contrast, the market beta in equation (7) is obtained from a one-dimensional model that considers only market shocks.

## 4. Data and local proxies

### Data

Our model was applied to the Polish banking sector, focusing on eight listed banks identified as systemically important (O-SII): Bank Millennium, BNP Paribas Bank Polska, Citi Handlowy, ING Bank Śląski, mBank, Pekao SA, PKO BP, and Santander Bank Polska. Prior to 2015, the financial system

is represented as a weighted aggregation of the banks' market capitalisations. From 2015 onwards, systemic importance is evaluated using scores aligned with the Polish Financial Supervision Authority's (Komisja Nadzoru Finansowego, KNF) methodology, consistent with the EBA/GL/2014/102 guidelines.

The empirical dataset covers the period January 2005 to December 2023 and includes stock price data for the selected banks and proxies for external shocks: market shocks, transition climate risks, and physical climate risks, all adapted to the Polish context. Stock price data were sourced from LSEG (formerly Refinitiv Eikon), while meteorological data were obtained from the Institute of Meteorology and Water Management (IMGW). To facilitate comparison with international studies, all financial variables are expressed in EUR, using the values downloaded directly from Reuters. The GJR-DCC--GARCH model was estimated on the full sample using monthly observations and quasi-maximum likelihood methods. Therefore, the results should be interpreted as ex-post measurements, not real--time forecasts.

## Market proxy for the Polish financial system

To define the market shock threshold $\theta^M$, we employ the broad Warsaw Stock Exchange Index (WIG) with quantile $q = 1\%$, consistent with the stress testing framework outlined by the European Banking Authority (EBA 2020). The estimated threshold is $\theta^M = 44\%$.

## Transition climate proxy for Poland

We construct the transition climate risk proxy based on a stranded asset portfolio, following the methodology of Jung, Engle, and Berner (2023; 2025), adapted to the Polish context. It includes indices that represent key Polish energy and mining companies significantly exposed to risks arising from the transition to a low-emission economy. Our portfolio consists of a long position in the WIG-Mining sector index (70%) and the WIG-Fuels sectoral index (30%), offset by a short position in the broad WIG index. This hedge eliminates the general market component, allowing residual returns to better reflect sector-specific exposure to transition-related risks. Since the WIG-Mining and WIG-Fuels indices were launched on 31 December 2010, and 31 December 2005, respectively, we reconstruct earlier data following the official WIG Index Methodology (GPW 2017). We identify shocks based on extreme negative deviations of the portfolio's residual returns relative to a chosen threshold $\theta^{Tr} = 60\%$, corresponding to the 1% quantile.

By analysing cumulative portfolio returns (Figure 1), we capture market-based adjustments to transition risk exposure. A decline in the cumulative return indicates rising transition risk, for example, due to falling profitability of carbon-intensive sectors. Temporary upward movements, such as during the Covid-19 pandemic and the escalation of the war in Ukraine, reflect short-term repricing driven by global supply shocks. It is important to note that while the broad market index adjustment eliminates market fluctuations, other factors unrelated to transition risk may still contribute to residual volatility, including the impact of state ownership, commodity price shocks unrelated to transition risk, and sector-specific events.

### Physical climate proxy for Poland

To estimate the physical climate risk factor, we define the external shocks as the deviation of the 12-month rolling average temperature in Poland from the 30-year baseline average obtained from the IMGW (Figure 2). For each month *t*, we compute the 12-month rolling average temperature and subtract the corresponding 30-year monthly average, obtaining a standardised anomaly index. We then calculate log differences of this index to obtain the monthly series of shocks. A physical climate risk event is identified when the temperature anomaly exceeds a certain threshold, represented as the quantile $r_t^{Ph} > \theta^{Ph}$. We use the 1%, upper-tail quintile, for which the estimated threshold is $\theta^{Ph} = 49\%$.

### Contribution of external factors

To evaluate the contribution of each external factor to systemic risk volatility, including the market, transition climate and physical climate shocks, we follow the methodology of Muhlack, Soost, and Henrich (2022). This approach allows us to assess the relative importance of market, transition, and physical climate shocks in driving fluctuations in the systemic risk measure.

To estimate beta factors and LRMES for the joint transition and physical climate systemic risk measure $S\left|Tr\right|PhCRISK_{i,t}$ we set the following thresholds at the 1% quantile: $\theta^{M} = 44\%$ for the market shocks, $\theta^{Tr} = 60\%$ for transition climate shocks, and $\theta^{Ph} = 49\%$ for physical climate shocks.

## 5. Empirical results of model implementation

In this study we use a GJR-GARCH model for univariate conditional variances combined with a DCC model to capture time-varying correlations. This specification provides a framework suitable for the relatively short time series available for the Polish banking sector, avoiding the overparameterisation problems associated with more general multivariate GARCH models such as BEKK. The DCC model was estimated on the full sample using monthly observations and quasi-maximum likelihood methods. Therefore, the results should be interpreted as ex-post measurements, not real-time forecasts.

### Beta estimation

Using procedure (18)–(19), we estimate beta coefficients that determine the contribution of market, transition, and physical climate shocks to the systemic risk measure defined in (16). These coefficients capture how sensitive each bank's equity returns are to specific sources of stress and thus form the direct transmission channel between climate exposures and capital shortfalls. For banks with financial assets exposed to transition risk, the expected sign of the transition climate beta is positive, as declines in stranded asset values reduce solvency and increase systemic risk. By contrast, the physical climate beta is expected to be negative, reflecting the weakening of banks' solvency under higher temperatures and physical climate stress. Importantly, the magnitude and persistence of these betas determine the strength with which climate shocks transform into the systemic risk measure and the resulting capital buffer shortfalls. Time-varying estimates of market beta $\beta_{i,t}^{M}$, transition climate beta $\beta_{i,t}^{Tr}$ and physical climate beta $\beta_{i,t}^{Ph}$ for the eight systemically important Polish banks are presented in Appendix.

## Joint transition and physical climate systemic risk measure

The joint systemic risk measure $S|Tr|PhCRISK_{i,t}$, which incorporates market, transition and physical climate risk, is typically higher than the systemic risk measure calculated in isolation (see Figure 11). The values shown in Figure 3 are ex-post model-implied estimates of conditional capital shortfall under simultaneous market, transition, and physical climate shocks over a six-month horizon. We report only positive values of $S|Tr|PhCRISK$, as negative values indicate no shortfall (surplus capital), which is not the focus of our risk analysis and is not assumed to be redistributed across institutions in stress periods.

Our extended measure, which captures the impact of rising climate risk – both transition and physical – confirms the influence of climate risk on the Polish banking system, which is underestimated when using a narrower measure like SRISK. Our analysis shows that the Polish banking system is vulnerable to climate-related shocks, including disruptions caused by stranded asset portfolios and temperature anomalies. This systemic fragility becomes especially pronounced during periods of turbulence, such as the Covid-19 pandemic or the war in Ukraine.

## Transition and physical climate risk measure in isolation from market shocks

Figure 4 illustrates the ex-ante capital buffer (in billion EUR) required by the banking system in response to a transition and physical climate shock, isolated from market shocks, over the next six months. The $Tr|PhCRISK$ measure reveals a growing vulnerability of the Polish banking system to losses related to stranded assets and temperature indices during the Covid-19 pandemic and the war in Ukraine. Interestingly, smaller banks (in the analysed cohort) such as mBank, Bank Millennium, and (until 2018) BNP Paribas exhibited heightened sensitivity in their asset returns.

During crises (global financial crisis 2008–2009, Covid-19 pandemic, invasion of Ukraine) we observe a high value of the $Tr|PhCRISK$ measure, as undercapitalised banks are more exposed to all types of risks (including climate shocks). Although all banks faced undercapitalisation during the Covid-19 period, the system's response to the war in Ukraine was less severe. This weaker reaction can be attributed to efforts to ensure energy independence and the rising preference for assets categorised as 'brown'. It is important to note that this study focuses specifically on the Polish market and the response of Polish banks' assets to the valuation of a stranded asset portfolio, whose returns often reflect domestic energy policies rather than global trends (Figure 1). In addition, temperature deviations from the long-term average during the study period (Figure 2) increasingly affected the banking system's sensitivity to climate shocks. The war in Ukraine and the resulting energy crisis, especially in Europe, focused market attention on energy security and supply chain disruptions, temporarily overshadowing concerns about rising temperatures.

## Decomposition of the isolated joint transition and physical climate risk measure

To better understand what drives changes in $Tr \mid PhCRISK_i$ for each of the eight banks, we decompose the difference into three components following Jung, Engle, and Berner (2023, 2025):

$$\Delta Tr \mid PhCRISK_i = \overbrace{k \cdot \Delta D_i}^{dDEBT} - \overbrace{\left(1-k\right) \cdot \Delta V_i \cdot \left(1-LRMES_{i,t-1}^{Tr}\right)\left(1-LRMES_{i,t-1}^{Ph}\right)}^{dEQUITY} + \\ + \overbrace{\left(1-k\right) \cdot V_{i,\,t-1} \cdot \left(\Delta LRMES_i^{Tr} + \Delta LRMES_i^{Ph} - \Delta LRMES_i^{Tr} \cdot \Delta LRMES_i^{Ph}\right)}^{dRISK} \tag{22}$$

where:

$$\Delta Tr \mid PhCRISK_i = Tr \mid PhCRISK_{i,t} - Tr \mid PhCRISK_{i,t-1}$$

$$\Delta D_i = D_{i,t} - D_{i,t-1}$$

$$\Delta LRMES_i = LRMES_{i,t} - LRMES_{i,t-1}$$

The first component, *dDEBT*, represents the contribution of a bank's debt to systemic climate risks, with higher debt levels increasing exposure to both transition and physical climate risks. The second component, *dEQUITY*, captures the impact of a bank's capital in mitigating climate risk, where declining market capitalisation heightens vulnerability to shocks. The third component, *dRISK*, reflects how changes in the climate betas affect $Tr|PhCRISK$, indicating the differential impact of various climate risks on the bank's overall stability.

The decomposition of changes in transition and physical climate (Appendix) highlights the contribution of individual factors to capital shortages during crisis periods. The Covid-19 pandemic is analysed in the first month after the lockdown, in April 2020 (Table 1), and during the peak capital shortage in October 2020 (Figure 5, Table 2) relative to the end of 2019. Similarly, for the war in Ukraine, the analysis covers the month after the invasion in March 2022 (Table 3) and the peak shortage period in October 2022 (Figure 6, Table 4) relative to the end of 2021. In both cases, the primary driver of the increase in systemic climate risks $Tr|PhCRISK$ was equity deterioration *dEQUITY*.

However, the situation was different in June 2023 (Figure 7, Table 5) and in December 2023, both relative to December 2022 (Table 6), when rising bank share values contributed to a reduction in climate risk changes. It is important to focus on the factors that intensify risks arising from increasing temperatures and the devaluation of stranded assets. Only through decomposition of $\Delta Tr|PhCRISK_i$ can we properly identify the growing significance of climate risk, as it would otherwise be covered by rising stock prices.

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.

## 6. Concluding remarks

In recent years, the connection between climate change and financial stability has become a pivotal point in policy discussions and academic research (Curcio, Gianfrancesco, Vioto 2023). From the systemic risk, the implications of transition and physical climate events require further investigation. In this study, we examine how the Polish banking sector of systemically important institutions responds

to climate shocks, using temperature anomalies as a proxy for physical risks, a stranded assets index for transition risks, and market index declines for financial shocks. We estimate banks' sensitivities using a multivariate GJR-DCC-GARCH model, which captures the time-varying relationships between market and climate factors, and construct a composite measure of systemic vulnerability.

Our study highlights the value of a multidimensional approach to assessing systemic risk. By jointly considering transition and physical climate factors, we capture interactions that would be missed when examining these risks in isolation. Using publicly available regional data, we show that climate risks are critical components of systemic vulnerability.

Our findings demonstrate that climate change and financial stability are closely linked. Both temperature anomalies and stranded asset portfolio performance impact systemic risk in Polish banks, although not all types of climate shocks have a significant impact. Measuring physical climate risk is inherently challenging because temperature anomalies are persistent and can impact financial stability through nonlinear channels. Consequently, physical risks can cause significant losses that spread throughout the financial system, and exposure to carbon-intensive sectors further increases systemic vulnerability. These results provide practical implications for policymakers seeking to mitigate the financial impacts of climate change-related phenomena.

We acknowledge that the GJR-DCC-GARCH model has limitations, particularly in capturing spillover effects between conditional variances of market and climate factors. While our approach identifies the joint dynamics of transition and physical climate risks, it may underestimate the magnitude of interactions under extreme stress. Future research could extend this framework using more general models to better capture cross-factor spillovers and richer dynamics.

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# Appendix

## Betas for the systemic transition climate and physical climate risk measure

Figure 1
Cumulative return of the stranded asset portfolio for Poland

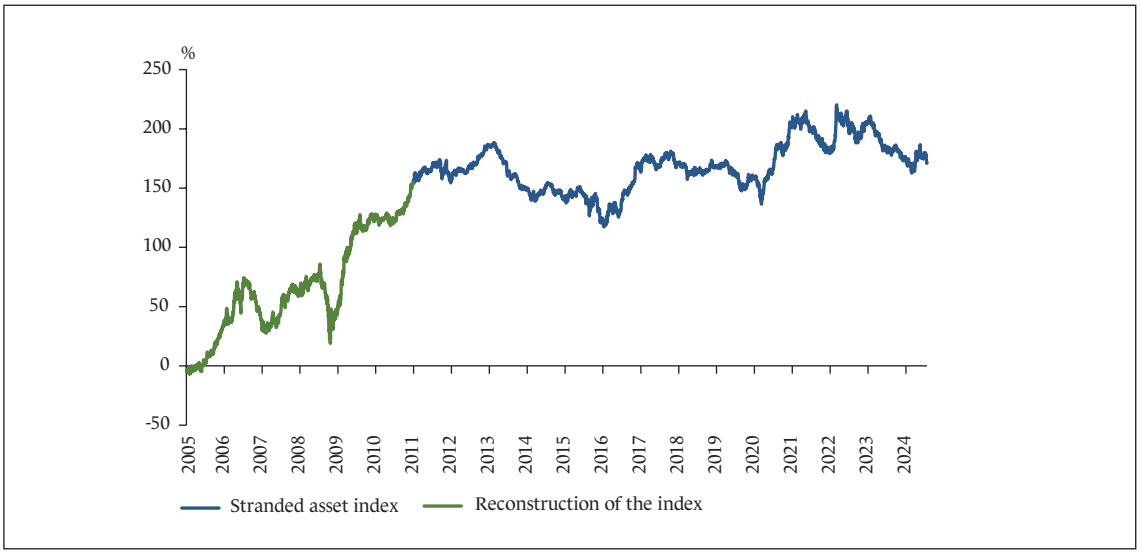



Figure 2
The temperature anomaly of 12-month rolling average temperature from the 30-year baseline average for Poland (in Celsius degrees)

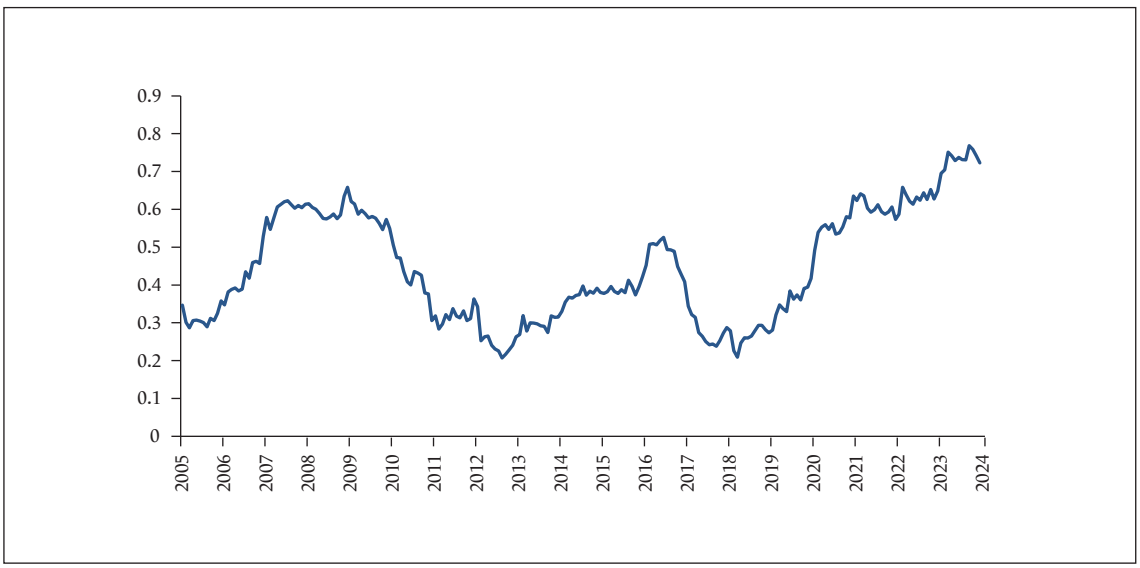
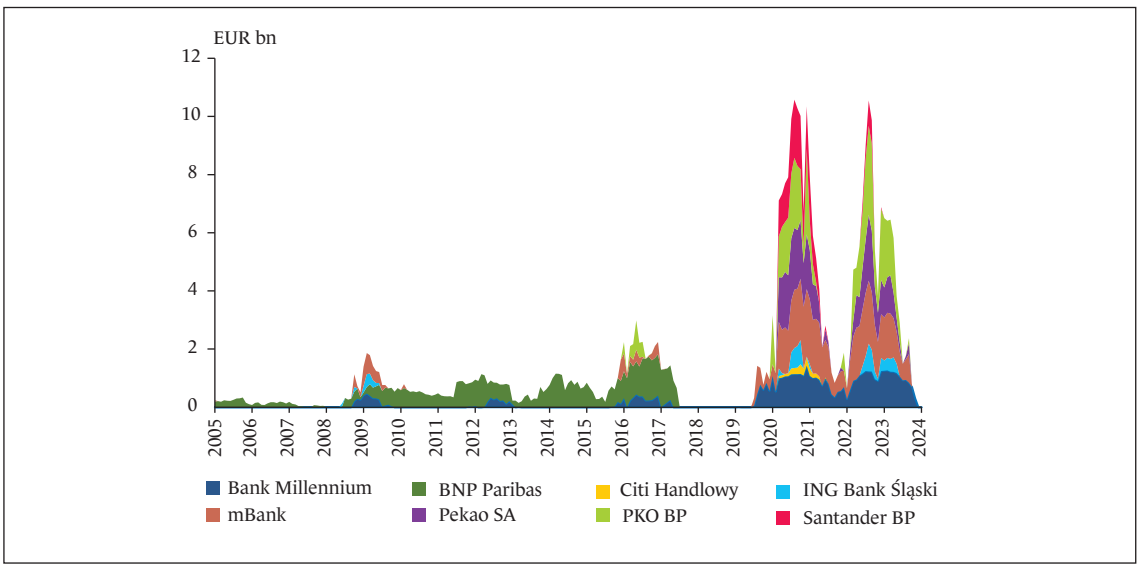


Figure 3

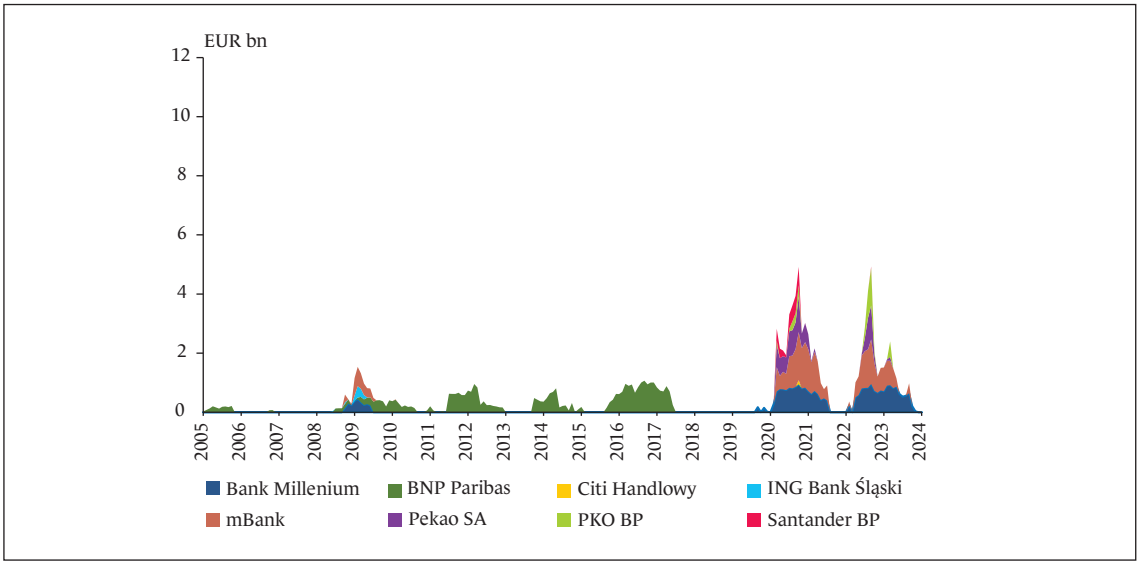
Joint systemic risk measure for the Polish systemically important banks incorporating market, transition, and physical climate shocks




Notes:
The figure shows ex-post values estimated over a six-month horizon. Beta coefficients for market, transition, and physical climate risk factors are obtained from a multidimensional DCC-GARCH model with thresholds defined at the 1% quantile: $\theta^{M} = 44\%, \theta^{Tr} = 60\%, \theta^{Ph} = 49\%$. Negative values, indicating surplus capital, are excluded from the analysis.

Figure 4

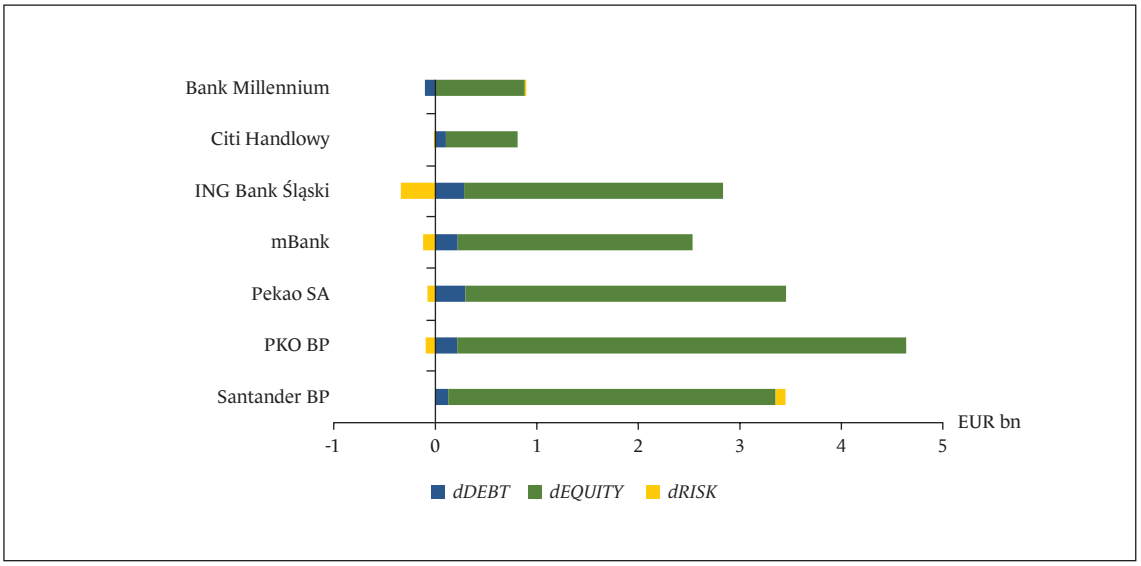
Transition and physical climate systemic risk measure for Polish systemically important banks in isolation from market shocks




Notes:
The figure shows ex-post values estimated over a six-month horizon with LRMES under market shocks set to zero $LRMES^{M}_{i,t} = 0$. Beta coefficients for market, transition, and physical climate risk factors are obtained from a multidimensional DCC-GARCH model with thresholds defined at the 1% quantile: $\theta^{M} = 44\%, \theta^{Tr} = 60\%, \theta^{Ph} = 49\%$. Negative values, indicating surplus capital, are excluded from the analysis.

Figure 5

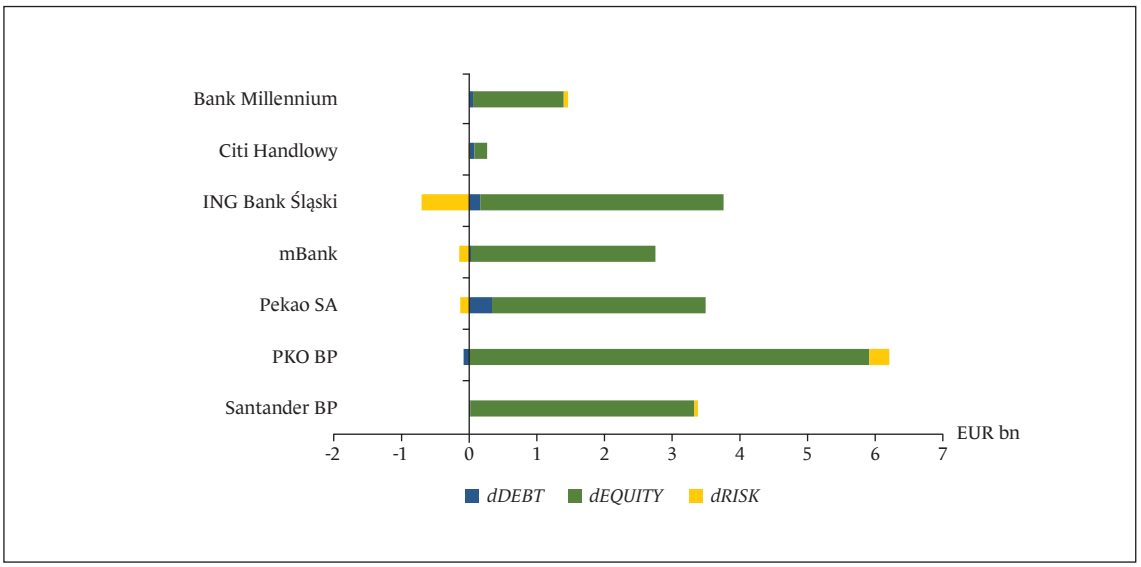
Decomposition of changes in transition and physical climate risk for Polish systemically important banks during the Covid-19 peak (October 2020 relative to December 2019)




Notes:
The figure shows the contributions of changes in debt (*dDEBT*), equity (*dEQUITY*), and residual risk (*dRISK*) to the total change in *Tr|PhCRISK*. Positive values indicate an increase in risk exposure, while negative values indicate risk reduction.

Figure 6

Decomposition of changes in transition and physical climate risk for Polish systemically important banks during the Ukraine war peak (October 2022 relative to December 2021)




Notes:
The figure shows the contributions of changes in debt (*dDEBT*), equity (*dEQUITY*), and residual risk (*dRISK*) to the total change in *Tr|PhCRISK*. Positive values indicate an increase in risk exposure, while negative values indicate risk reduction.

Figure 7
Decomposition of changes in transition and physical climate risk for Polish systemically important banks between December 2022 and June 2023




Notes:
The figure shows the contributions of changes in debt (*dDEBT*), equity (*dEQUITY*), and residual risk (*dRISK*) to the total change in *Tr|PhCRISK*. Positive values indicate an increase in risk exposure, while negative values indicate risk reduction.

Figure 8
Market betas for Polish banks

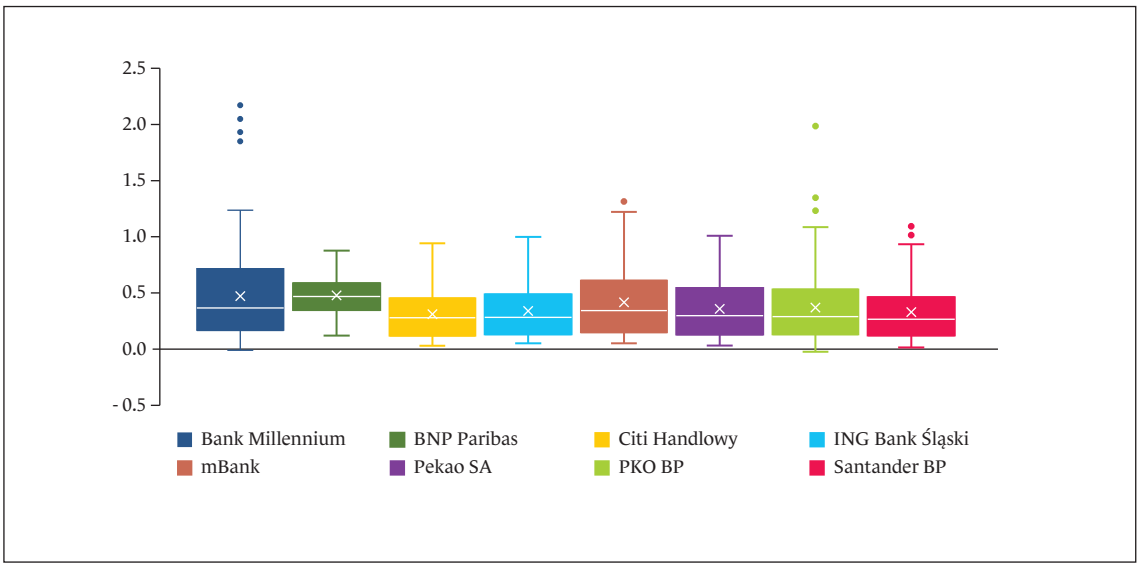


Figure 9
Transition climate betas for Polish banks

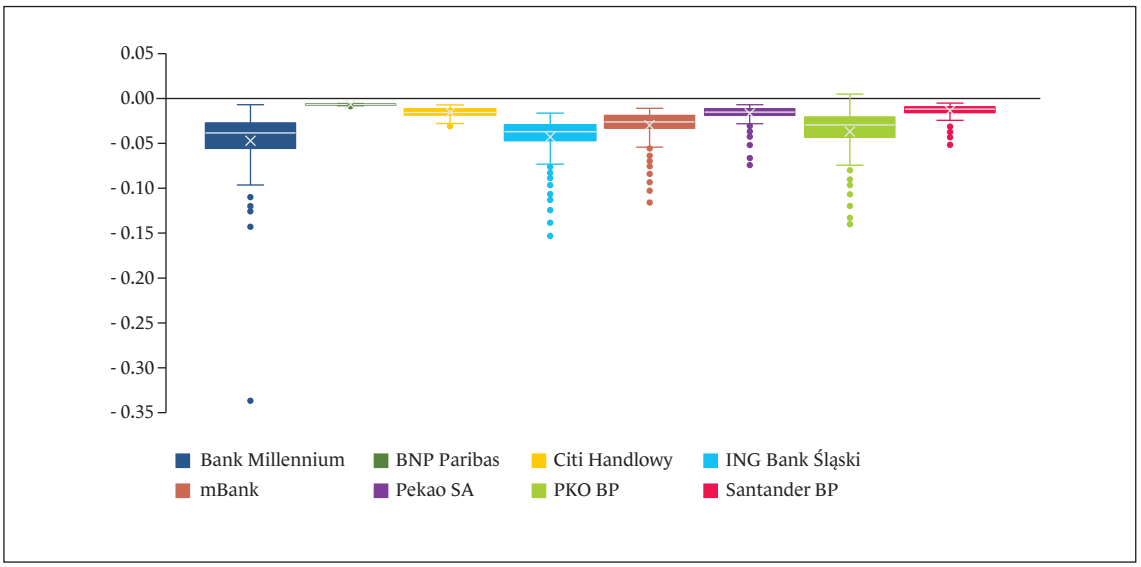
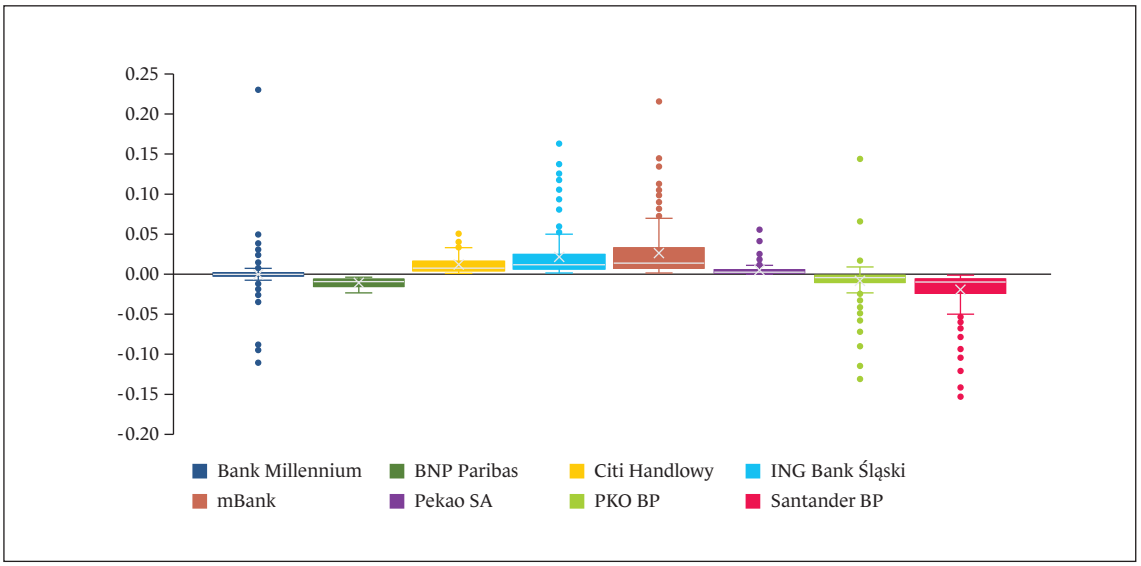


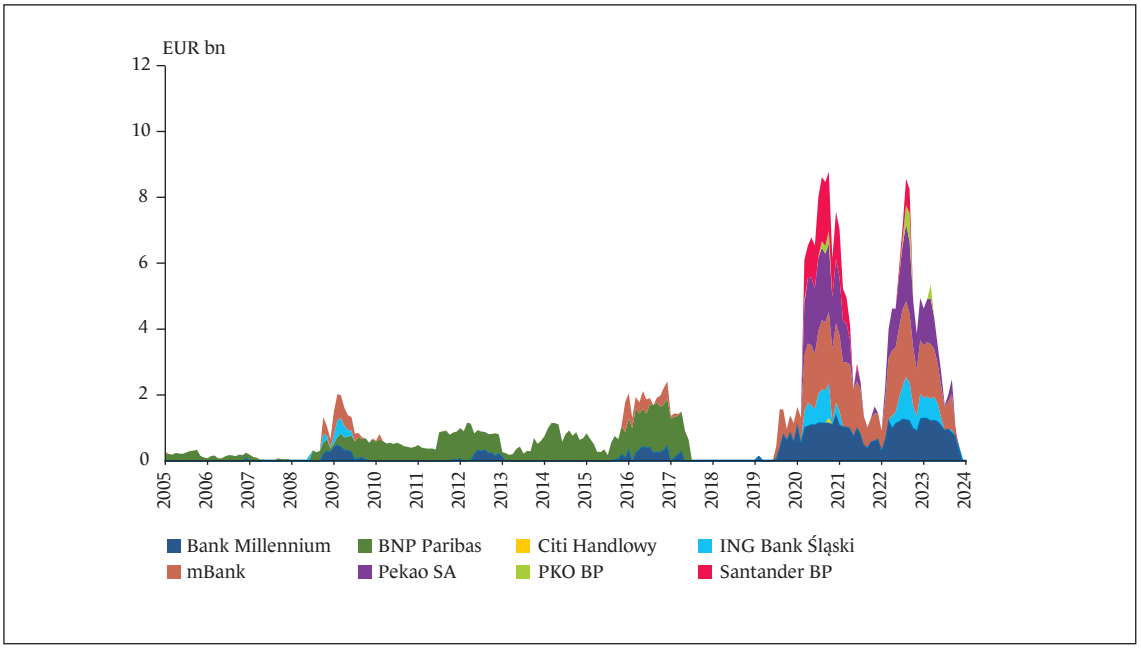

Figure 10
Physical climate betas for Polish banks



## Systemic risk measure in isolation

The systemic risk estimated in isolation of climate shocks (Figure 11) is similar in magnitude to the values reported by V-Lab for Poland and broadly consistent with the results presented in the semi-annual Financial Stability Report of Narodowy Bank Polski (NBP 2024). However, it should be noted that our measure is not identical to SRISK, as the beta coefficients are derived from a multidimensional GARCH specification that explicitly incorporates transition and physical climate risk factors in addition to the market component.

Figure 11
Systemic risk measure for Polish systemically important banks in isolation from climate shocks




Notes:
The figure shows ex-post values estimated over a six-month horizon with LRMES under transition and physical climate shocks set to zero $LRMES^{Tr}_{i,t} = LRMES^{Ph}_{i,t} = 0$. Beta coefficients for market, transition, and physical climate risk factors are obtained from a multidimensional DCC-GARCH model with thresholds defined at the 1% quantile: $\theta^{M} = 44\%$, $\theta^{Tr} = 60\%$, $\theta^{Ph} = 49\%$. Negative values, indicating surplus capital, are excluded from the analysis.

## Climate RISK decomposition for Polish systemically important banks

$dCRISK = CRISK(t) - CRISK(t-1)$ is a change of an isolated transition climate and physical climate systemic risk, where $CRISK(t) = Tr \mid PhCRISK_{i,t}$ is an isolated transition climate and physical climate systemic risk for the $i$-th bank at the moment $t$. *dDEBT* is the contribution of the bank's debt to *CRISK*. *dEQUITY* is the contribution of the bank's equity position on *CRISK*. *dCRISK* is the contribution of increase in climate betas to *CRISK*. All amounts are in EUR bn.

Table 1

CRISK change decomposition for Polish systematically important banks, December 2019 – April 2020 (first month after the Covid-19 lockdown)

| Bank | *CRISK*(*t* – 1) | *CRISK*(*t*) | *dCRISK* | *dDEBT* | *dEQUITY* | *dRISK* |
|---|---|---|---|---|---|---|
| Bank Millennium | 0.15 | 0.70 | 0.55 | -0.12 | 0.67 | -0.01 |
| Citi Handlowy | -0.66 | -0.19 | 0.47 | 0.09 | 0.39 | -0.01 |
| ING Bank Śląski | -2.92 | -0.86 | 2.05 | 0.25 | 1.96 | -0.16 |
| mBank | -0.79 | 0.82 | 1.61 | 0.19 | 1.53 | -0.11 |
| Pekao SA | -2.18 | 0.75 | 2.93 | 0.26 | 2.71 | -0.04 |
| PKO BP | -4.15 | 0.15 | 4.30 | 0.16 | 4.26 | -0.11 |
| Santander BP | -2.83 | 0.40 | 3.23 | 0.09 | 3.05 | 0.09 |
| SUM | -13.37 | 1.77 | 15.15 | 0.93 | 14.58 | -0.36 |

Notes:
*CRISK*(*t* – 1) reports the value of the isolated joint transition and physical climate risk in December 2019, while *CRISK*(*t*) refers to the corresponding value in April 2020. Positive values (in EUR bn) indicate additional capital required to survive shocks, whereas negative values imply no additional capital is needed.

Table 2

CRISK change decomposition for Polish systematically important banks, December 2019 – October 2020 (Covid-19 peak capital shortage)

| Bank | *CRISK*(*t* – 1) | *CRISK*(*t*) | *dCRISK* | *dDEBT* | *dEQUITY* | *dRISK* |
|---|---|---|---|---|---|---|
| Bank Millennium | 0.15 | 0.95 | 0.79 | -0.10 | 0.88 | 0.01 |
| Citi Handlowy | -0.66 | 0.14 | 0.80 | 0.10 | 0.71 | -0.01 |
| ING Bank Śląski | -2.92 | -0.42 | 2.50 | 0.28 | 2.55 | -0.34 |
| mBank | -0.79 | 1.63 | 2.42 | 0.22 | 2.31 | -0.12 |
| Pekao SA | -2.18 | 1.19 | 3.38 | 0.30 | 3.16 | -0.08 |
| PKO BP | -4.15 | 0.39 | 4.54 | 0.21 | 4.42 | -0.09 |
| Santander BP | -2.83 | 0.62 | 3.45 | 0.13 | 3.23 | 0.10 |
| SUM | -13.37 | 4.50 | 17.87 | 1.14 | 17.26 | -0.53 |

Notes:
*CRISK*(*t* – 1) reports the value of the isolated joint transition and physical climate risk in December 2019, while *CRISK*(*t*) refers to the corresponding value in October 2020.

Table 3

CRISK change decomposition for Polish systematically important banks, December 2021 – March 2022 (a month after the invasion in Ukraine)

| Bank | *CRISK*($t-1$) | *CRISK*($t$) | *dCRISK* | *dDEBT* | *dEQUITY* | *dRISK* |
|---|---|---|---|---|---|---|
| Bank Millennium | -0.51 | 0.23 | 0.74 | 0.06 | 0.68 | 0.00 |
| Citi Handlowy | -0.64 | -0.44 | 0.20 | 0.08 | 0.11 | 0.01 |
| ING Bank Śląski | -3.72 | -2.66 | 1.06 | 0.18 | 0.88 | 0.01 |
| mBank | -1.10 | 0.13 | 1.23 | 0.04 | 1.18 | 0.01 |
| Pekao SA | -2.21 | -1.07 | 1.14 | 0.35 | 0.82 | -0.03 |
| PKO BP | -4.86 | -2.86 | 1.99 | -0.06 | 2.41 | -0.36 |
| Santander BP | -3.34 | -2.06 | 1.28 | 0.03 | 1.30 | -0.05 |
| SUM | -16.37 | -8.74 | 7.64 | 0.68 | 7.37 | -0.41 |

Notes:
*CRISK*($t-1$) reports the value of the isolated joint transition and physical climate risk in December 2021, while *CRISK*($t$) refers to the corresponding value in March 2022.

Table 4

CRISK change decomposition for Polish systematically important banks, December 2021 – October 2022 (Ukraine war peak capital shortage)

| Bank | *CRISK*($t-1$) | *CRISK*($t$) | *dCRISK* | *dDEBT* | *dEQUITY* | *dRISK* |
|---|---|---|---|---|---|---|
| Bank Millennium | -0.51 | 0.95 | 1.46 | 0.06 | 1.34 | 0.06 |
| Citi Handlowy | -0.64 | -0.39 | 0.25 | 0.08 | 0.19 | -0.01 |
| ING Bank Śląski | -3.72 | -0.67 | 3.06 | 0.16 | 3.59 | -0.70 |
| mBank | -1.10 | 1.51 | 2.60 | 0.03 | 2.72 | -0.15 |
| Pekao SA | -2.21 | 1.15 | 3.36 | 0.34 | 3.16 | -0.13 |
| PKO BP | -4.86 | 1.27 | 6.12 | -0.08 | 5.91 | 0.30 |
| Santander BP | -3.34 | 0.04 | 3.38 | 0.01 | 3.31 | 0.05 |
| SUM | -16.37 | 3.87 | 20.24 | 0.59 | 20.23 | -0.58 |

Notes:
*CRISK*($t-1$) reports the value of the isolated joint transition and physical climate risk in December 2021, while *CRISK*($t$) refers to the corresponding value in October 2022.

Table 5

CRISK change decomposition for Polish systematically important banks, December 2022 – June 2023

| Bank | *CRISK*(*t* – 1) | *CRISK*(*t*) | *dCRISK* | *dDEBT* | *dEQUITY* | *dRISK* |
|---|---|---|---|---|---|---|
| Bank Millennium | 0.66 | 0.86 | 0.20 | 0.32 | -0.11 | 0.00 |
| Citi Handlowy | -0.94 | -1.26 | -0.31 | 0.08 | -0.26 | 0.02 |
| ING Bank Śląski | -1.25 | -0.77 | 0.48 | 0.53 | -0.27 | 0.22 |
| mBank | 0.54 | 0.29 | -0.26 | 0.43 | -0.77 | 0.08 |
| Pekao SA | -0.06 | -0.79 | -0.73 | 0.50 | -1.27 | 0.04 |
| PKO BP | -0.53 | -0.93 | -0.40 | 1.39 | -1.76 | -0.02 |
| Santander BP | -1.47 | -3.32 | -1.85 | 0.42 | -2.23 | -0.04 |
| SUM | -3.05 | -5.93 | -2.87 | 3.66 | -6.68 | 0.30 |

Notes:
*CRISK*(*t* – 1) reports the value of the isolated joint transition and physical climate risk in December 2022, while *CRISK*(*t*) refers to the corresponding value in June 2023.

Table 6

CRISK change decomposition for Polish systematically important banks, December 2022 – December 2023

| Bank | *CRISK*(*t* – 1) | *CRISK*(*t*) | *dCRISK* | *dDEBT* | *dEQUITY* | *dRISK* |
|---|---|---|---|---|---|---|
| Bank Millennium | 0.66 | 0.03 | -0.63 | 0.40 | -1.03 | 0.01 |
| Citi Handlowy | -0.94 | -1.63 | -0.68 | 0.12 | -0.68 | 0.02 |
| ING Bank Śląski | -1.25 | -3.17 | -1.92 | 0.68 | -2.77 | 0.16 |
| mBank | 0.54 | -1.58 | -2.13 | 0.58 | -2.73 | 0.03 |
| Pekao SA | -0.06 | -3.33 | -3.27 | 0.68 | -3.98 | 0.03 |
| PKO BP | -0.53 | -5.06 | -4.52 | 1.69 | -6.19 | -0.03 |
| Santander BP | -1.47 | -6.55 | -5.08 | 0.58 | -5.62 | -0.04 |
| SUM | -3.05 | -21.29 | -18.23 | 4.74 | -23.00 | 0.18 |

Notes:
*CRISK*(*t* – 1) reports the value of the isolated joint transition and physical climate risk in December 2022, while *CRISK*(*t*) refers to the corresponding value in December 2023.

# Ryzyko systemowe a zmiany klimatyczne: łączny wpływ ryzyka transformacji i ryzyka fizycznego na polski sektor bankowy


## Streszczenie

Zmiany klimatyczne wprowadzają nowe źródła niepewności dla stabilności systemu finansowego, obejmujące zarówno ryzyko fizyczne, wynikające z ekstremalnych zjawisk pogodowych i anomalii klimatycznych, jak i ryzyko przejścia, związane z transformacją gospodarczą w kierunku niskoemisyjnym. Oba wymiary mogą silnie oddziaływać na sektor bankowy i w konsekwencji na stabilność finansową całej gospodarki.

Celem badania jest ocena wpływu ryzyka klimatycznego na stabilność polskiego systemu bankowego. Punktem wyjścia jest hipoteza, że łączny pomiar ryzyka przejścia i ryzyka fizycznego dostarcza pełniejszej oceny ryzyka systemowego niż analiza każdego z tych wymiarów oddzielnie. Zakładamy, że wspólne ujęcie tych dwóch rodzajów ryzyka pozwala zidentyfikować okresy zwiększonej podatności banków systemowo ważnych na szoki zewnętrzne.

W pracy rozszerzono dotychczas stosowane podejścia, wprowadzając trzeci wymiar ryzyka systemowego. W odróżnieniu od badań opartych na indeksach globalnych zastosowano lokalne miary dostosowane do polskiego rynku. Do pomiaru ryzyka fizycznego wykorzystano anomalie temperatury obliczane względem trzydziestoletniej średniej, natomiast ryzyko przejścia opisano za pomocą indeksu aktywów osieroconych skonstruowanego dla spółek wysokoemisyjnych notowanych na GPW.

Analiza obejmuje dane miesięczne dla ośmiu systemowo ważnych banków w Polsce w okresie od 2005 do 2023 r. Do oszacowania wrażliwości poszczególnych instytucji na szoki rynkowe i klimatyczne wykorzystano wielowymiarowy model GJR-DCC-GARCH, który umożliwia uchwycenie współzależności oraz ocenę łącznego wpływu czynników rynkowych, przejścia i fizycznych na ryzyko systemowe.

Wyniki wskazują, że zarówno anomalie temperatury, jak i indeks aktywów osieroconych oddziałują na ryzyko systemowe w polskim sektorze bankowym, przy czym znaczenie poszczególnych czynników zmienia się w czasie. W okresach kryzysów wpływ ryzyka klimatycznego na stabilność finansową wyraźnie wzrasta, a banki silnie zaangażowane w aktywa wysokoemisyjne są szczególnie narażone. Jednocześnie pomiar ryzyka fizycznego pozostaje wyzwaniem ze względu na trwałość anomalii temperatury oraz ich potencjalnie nieliniowy wpływ na system finansowy.

Wnioski z badania podkreślają znaczenie wielowymiarowego podejścia do oceny ryzyka systemowego. Łączne ujęcie ryzyka przejścia i ryzyka fizycznego pozwala uchwycić interakcje, które pozostają niewidoczne w analizach jednowymiarowych. Uzyskane rezultaty mają praktyczne znaczenie dla instytucji finansowych i wskazują na potrzebę uwzględniania ryzyka klimatycznego w standardowych narzędziach nadzorczych oraz polityce makroostrożnościowej.


**Słowa kluczowe:** ryzyko klimatyczne, stabilność finansowa, ryzyko systemowe, ryzyko przejścia, ryzyko fizyczne