Central European
Management
Journal

Received 22 May 2024
Revised 14 April 2025
Accepted 16 September 2025

# E-factor augmentation: a method to quantify the environmental factor in systemic risk analysis

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## Abstract

**Purpose** – The paper presents a new method that quantifies environmental risk in systemic risk measurement based on the exposure approach using an existing E-score as the source of information about bank exposure to environmental risks. Our method allows us to base the impact of environmental risk exposure on individual characteristics of banks and their systemic risk levels.

**Design/methodology/approach** – We extract the environmental factor (E-factor) from each bank's environmental score (part of the ESG score) and augment systemic risk measurement with it. We apply econometric systemic risk models to quantify systemic risk, and for each, we add the E-factor using a conditional sensitivity function. We demonstrate our method empirically on two systemic risk models: CoVaR and SRISK, using a sample of 20 systemically important European banks from 12 European countries between 2007 and 2023.

**Findings** – Our method captures a bigger impact of the environmental risk factor in periods of instability. Moreover, the E-factor records higher impacts on more fragile banks. This observation holds equally for banks from developed and emerging countries, regardless of whether they are global or local systemically important financial institutions. With the E-CoVaR and E-SRISK rankings constructed, we illustrate the contrasts between Western Europe and the CEE region. Higher environmental risk is quantified for the latter, with Russian, Romanian and Polish banks at the bottom of the environmental risk exposure ranking.

**Research limitations/implications** – The presented risk quantification methods are universal in the technical sense and applicable to other systemic risk measures and other environmental scores, while the ranking methods may be of value for the regulators as they allow them to identify the banks that are most prone to losses based on their systemic-risk-based environmental exposure.

**Practical implications** – Regulators and financial institutions can leverage the proposed ranking methods to identify environmentally vulnerable banks, encouraging them to implement more targeted interventions to mitigate climate-related financial risks. Enhanced monitoring of weak links and exposures within the banking sector can help regulators anticipate systemic disruptions and require banks to strengthen buffers against climate-induced shocks.

**Social implications** – Over the long term, this research could influence regulatory frameworks by encouraging the integration of climate risk considerations into financial stability assessments, ultimately reducing spillover effects and systemic crises that produce significant environmental and social costs.

**JEL Classification** — G21, Q51, C32

*Funding:* The National Science Center funded this research project under Agreement UMO-2018/29/N/HS4/02783.

Central European Management Journal
Vol. 34 No. 2, 2026
pp. 289-320
Emerald Publishing Limited
e-ISSN: 2658-2430
p-ISSN: 2658-0845
DOI 10.1108/CEMJ-05-2024-0172

**Originality/value** – The paper addresses a research gap by proposing a novel method of environmental risk measurement and its application to, inter alia, the CEE region.

**Keywords** Systemic risk, ESG, Risk management, Environmental risk, Econometric methods

**Paper type** Research article

## Introduction

Systemic risk has been increasing over the past 20 years. In that time, we have witnessed unprecedented growth of the banking systems across the world, the biggest financial crisis in history, and an unprecedented international-scale public debt crisis. Then, years of recession and negative interest rates followed, coupled with the global pandemic that froze economies and markets in a way unobserved before. Currently, we are witnessing spikes in inflation and energy prices across the world that may very well become the next driver of a systemic crisis. This makes systemic risk a fascinating and challenging topic for analysis, simultaneously making it a very important phenomenon to model using elaborate econometric tools.

An equally important research avenue is the impact of environmental risk on the financial systems, given that greenhouse gas emissions have caused the $CO_2$ concentration to increase at a rate approximately 200 times faster in the last 100 years than it occurred under natural conditions on Earth (Jędrak *et al.*, 2023). Its importance is driven by growing concerns over climate change, resource depletion and environmental degradation (Rekker, Ives, Wade, Webb, & Greig, 2022). The increasing frequency and severity of extreme weather events, regulatory shifts toward sustainability, and investor demand for environmentally responsible assets have heightened the need to assess how financial institutions and markets respond to these risks (Bischof, Laux, & Leuz, 2020). Climate-related financial risks, including transition and physical risks, can significantly impact asset valuations and credit risk (Jung, Engle, & Berner, 2021), firm formation and survival (Anton, 2024) and financial stability (Stolbov & Shchepeleva, 2022). Consequently, integrating environmental risk into financial decision-making has become essential for policymakers, investors and regulators, making it a pressing area for academic and empirical research in financial economics.

Most recent studies confirm that ESG scores capture climate risk impact on listed companies (e.g. Baer, Gasparini, Lancaster, & Ranger, 2023; Ding, Guo, & Tsai, 2024). Similarly, a few articles quantify the risk effects of carbon-related and climate risk factors on banks (Delis, de Greiff, Iosifidi, & Ongena, 2021; Altieri & Radev, 2023; Ali, Azmi, Kowsalya, & Rizvi, 2023). However, despite the ample evidence of the importance of quantifying the whole of environmental risk in systemic risk analysis, very few methods quantify it beyond climate risk. Moreover, when it comes to econometric methods of systemic risk measurement developed after the global financial crisis, none of such measures in their current shape include the larger environmental risk explicitly.

The primary purpose of this article is to present a new method that allows for adding the environmental risk factor (E-factor) to systemic risk measurement. Since current systemic risk measures do not quantify the E-factor, this was a critical research gap. The developments in systemic risk analysis of the last few years and the very new empirical research on the impact of the ESG factors on risk in the banking sector give the grounds for a meaningful introduction of the ESG-based E-factor to systemic risk analysis. Notably, although applied to $\Delta$CoVaR (Adrian & Brunnermeier, 2016) and SRISK (Brownlees & Engle, 2017; Engle, Emambakhsh, Manganelli, Parisi, & Pizzeghello, 2024) in this study, the solution that we propose is universal in the technical sense and applicable to other econometric systemic risk measures.

The study builds on the most recent publications regarding the nexus of systemic risk, banks and ESG scores. Several studies link the ESG performance and the quality of the assets in the banking industry (Alam, Kabir Hassan, & Banna, 2024; Cantero-Saiz, Polizzi, & Scannella, 2024), especially the aspects related to the credit portfolios (Abdelsalam, Azmi, Disli, & Kowsalya, 2023), losses (Bruno, Iacoviello, & Giannetti, 2024), liquidity (Gupta & Kashiramka, 2024) and financial distress (Citterio & King, 2023) of banks. At the same time, other studies indicate significant relationships between systemic risk and ESG scores in corporate firms (Anwer, Goodell, Migliavacca, & Paltrinieri, 2023) and financial institutions (Aevoae, Andrieş, Ongena, & Sprincean, 2023; Curcio, Gianfrancesco, Onorato, & Vioto, 2024).

Our article contributes to the literature on systemic risk measurement by integrating environmental risk into established financial risk models. Building on the exposure approach, we enhance systemic risk assessment by constructing and subsequently incorporating an environmental factor (E-factor) derived from banks' environmental scores, a component of the ESG score. We also developed beta-independent exposure-based ranking methods and applied them empirically. Our methods extend prior studies on ESG and financial stability by providing a systematic approach to quantifying the impact of environmental risk on systemic risk. The empirical application to four models ΔCoVaR, SRISK (baseline analysis), VaR and QLaR (robustness analysis), based on approx. 180,000 data entries offer novel insights into how environmental risk exposure varies across banks, regions and economic conditions, particularly during financial crises. Unlike previously proposed methods that focus on static ESG measures, our framework dynamically links environmental risk with systemic vulnerability, offering practical implications for regulators and policymakers in assessing financial institutions' resilience to environmental threats.

In the remaining part of the article, we present an overview of the most relevant literature, econometric methods and their empirical application to a diverse group of systemically important European banks. Next, we provide beta-independent exposure-based rankings of these institutions based on the varying impact of the E-factor on systemic risk in different periods, the discussion of the results and conclusions. We execute baseline estimation using the ΔCoVaR model, and we utilize the SRISK model in our robustness analysis. The article concludes with a discussion of the findings and the utility of potential applications of our approach.

## A brief overview of the current literature

### *Environmental risk and its measurement*

Systemic risk is a product of two wide sets of risk factors, namely institution-specific and market-specific. The first category refers to the internal characteristics of systemically important financial institutions that make them more susceptible to external shocks. The other category refers to all factors that make systems more likely to propagate such shocks (cf. Benoit, Colliard, Hurlin, & Pérignon, 2017; Silva *et al.*, 2017). Therefore, there is a strong argument for measuring (modeling) them using different econometric tools. Moreover, disentangling systemic risk into these two categories allows for measuring various important risk factors with better precision.

Research shows that crises slow down the transition toward a greener economy and significantly decrease the costs committed to investment in ecologically friendly solutions. Therefore, systemic risk management may – indirectly – add to the "green change" by lowering the costs of the potential financial crises and the likelihood of them materializing (ECB, 2022). Nonetheless, ecological factors play a more crucial role on the other side of the systemic risk equation, i.e. as the drivers of systemic risk. Thus, having reliable information on banks' exposure to environmental risk factors would benefit the regulators and the financial industry (cf. Toma & Stefanelli, 2022).

The most influential organizations that deal with environmental factors have recognized them as an essential part of systemic risk. Among other institutions, the Bank for International Settlements (2021), European Securities and Markets Authority (2022), European Systemic Risk Board (2021), European Banking Authority (2022) and the Financial Stability Oversight Council (2021) deem environmental changes and pollution an emerging threat to financial system stability. Likewise, central banks point to environmental risk factors in systemic risk reports (e.g. BoE, 2018; 2021, 2024; ECB, 2019; 2022; FSOC, 2021; International Monetary Fund, 2022) [1].

The literature draws much attention to climate change. For instance, the Bank of England (2018) describes three main channels via which climate risk impacts systemic risk. They include physical climate risks (especially the materialization of catastrophic risk), transition risks (risks to cash flows related to the transition toward green energy) and liability risks (related to potential compensation payouts). Similarly, BIS (2021) indicates that risk categories present in the Basel Framework (credit, market, liquidity and operational risk) are affected by climate change (cf. Nieto, 2017). Nevertheless, “there is a limited amount of research and accompanying data exploring how climate risk drivers feed into transmission channels and the financial risks banks face. The existing analysis does not generally translate changes in climate-related variables into changes in banks’ credit, market, liquidity, or operational risk exposures or bank balance sheet losses” (BIS, 2021, p. 2).

In recent years, the banking sector has adopted a broad and evolving set of methodologies to quantify climate-related financial risks. These methods aim to capture both physical risks, such as those arising from extreme weather events and transition risks, related to policy, legal, technological and market shifts associated with the transition to a low-carbon economy. A central approach is scenario analysis, which models how different climate futures – often derived from frameworks such as those provided by the Network for Greening the Financial System (NGFS, 2024), the International Energy Agency (IEA, 2024) or the Intergovernmental Panel on Climate Change (IPCC, 2023) – might impact a bank’s portfolio over time. These scenarios are typically structured around different temperature pathways (e.g., 1.5°C, 2°C or >3°C) and serve to assess the sensitivity of financial exposures to variables such as carbon pricing, energy transitions and physical climate shocks.

Closely related to scenario analysis is climate stress testing, which integrates climate-specific variables into traditional credit risk frameworks to simulate how a bank’s balance sheet would respond to climate-induced shocks. Wong and Ho (2023) propose a framework incorporating extreme weather events into models estimating the probability of default (PD) and loss given default for residential mortgages, demonstrating potentially significant portfolio losses. Nehrebecka (2021) presents a two-part workflow to assess climate risk impact on PD, combining sectoral and company-level analyses with stress testing. Monnin (2018) emphasizes the importance of forward-looking scenarios and complex cause-and-effect linkages in climate risk assessment, highlighting available methodologies for transition risk evaluation. Soběhart (2021) introduces an approach for quantifying climate risk uncertainty in competitive business environments, applicable to assessing business strategy risks and estimating PD under different scenarios. These studies collectively underscore the need for banks to incorporate climate risk variables into their financial risk assessment models to better understand and mitigate potential losses.

Brunetti *et al.* (2021) indicate that the shocks related to climate change and the degradation of the natural environment are significant from the micro- and macroprudential perspectives, and they are a source of risk for the economies and financial systems. Therefore, there is a need to further research the climate risk factors and their impact on bank exposure across all types of risk. Nevertheless, Battiston (2019) as well as Chenet, Ryan-Collins, and van Lerven (2021) argue that the emerging policy frameworks designed for dealing with climate-related financial risks are limited in impact because such types of risks are radically uncertain, which means that efficient price discovery is very challenging. On a similar note, Toma and Stefanelli (2022) claim that there are no proposals of an analytical framework for combating climate risk using financial management and internal control tools.

Several researchers contributed to the methodological development of climate risk tools. Monasterolo (2020) proposed a forward-looking Climate Value-at-Risk (Climate VaR) metric that quantifies the potential decline in portfolio value due to climate transition and physical risks. Climate VaR incorporates scenario-based inputs and is increasingly applied in portfolio management and strategic asset allocation. Campiglio, Daumas, Monnin, and Von Jagow

(2023) explored how climate-related events impact asset pricing, proposing methods to link macroeconomic shocks and financial revaluation channels. Battiston, Dafermos, and Monasterolo (2021) focused on integrating climate risk into systemic risk frameworks, highlighting methodological challenges including deep uncertainty, non-linear dynamics and the complex interdependence of physical and transition risks. Jourde and Moreau (2022) developed a market-based framework to assess which financial institutions are most vulnerable to transition risks.

Physical risk mapping complements these transition-focused tools by assessing how exposed collateral (e.g. in mortgage or infrastructure lending) is to environmental hazards such as flooding, wildfire, sea level rise or extreme heat. Often, such methods combine asset allocation data with hazard maps derived from climate models and geospatial analysis tools (Hoehn, Salzberger, & Bienert, 2025; Bienert and Höhn, 2023). Various banks also develop internal climate risk models, which embed climate-related variables directly into proprietary risk engines for credit, market and operational risk. These models often combine external climate datasets with internal loan, sector and geographic data, allowing for more precise quantification of exposure and sensitivity to climate risk factors (Georgopoulou *et al.*, 2015).

Emerging technologies also contribute new capabilities to climate risk quantification. Scholars explore machine learning and AI-based predictive modeling for identifying patterns and forecasting climate risk impacts with higher precision (Ferrara, Ciano, Capriotti, & Muzzioli, 2024). These tools are particularly useful for integrating large-scale unstructured data (e.g., satellite imagery, climate news and emissions disclosures) into risk models. Moreover, researchers test blockchain technologies for improving transparency and traceability in climate-related financial data. Furthermore, scholars augment traditional catastrophe models used in insurance to simulate financial losses under climate change scenarios, supporting regulatory exercises (Latchman, Clarke, Zapatka, Sousounis, & Stransky, 2020).

Thus far, the use of econometric methods in researching the direct impact of climate-related risk factors on systemic risk is limited. Moreover, even simpler quantitative econometric methods that capture climate and other environmental risks in systemic risk analysis are scarce. Among the few quantitative empirical studies, we may find the one by Battiston *et al.* (2021), who investigated the spill-over of risk in stylized networks and reported that the risks generated by climate-related events can be systemic. On a related note, Alvarez, Cocco, and Patel (2020) discuss a method of merging climate risk categories with traditional financial risk metrics to evaluate their contribution to systemic risk.

One other significant study is that of Jung *et al.* (2021), who proposed a model called CRISK, a method of calculating the impact of climate risk (mainly brown emissions-based exposure) on systemic risk. The authors estimate individual institutions' betas that relate directly to their exposures in the brown fuels markets and use the SRISK model as the base for incorporating climate risk exposure into systemic risk measurement. This approach has several benefits, a major one being the ability to estimate individual betas of financial institutions. Nonetheless, the method uses confidential data that is not easily available, even to the regulators, which makes it costly and time-consuming to obtain, particularly for Europe. Moreover, it considers only a fraction of the environmental risk exposure, disregarding other environmental factors beyond climate risk. For many European financial institutions, such a narrow scope is insufficient for systemic risk analysis.

Several authors researched the link between green finance and larger-scale risk and its impact on societies. For instance, Sohag, Hammoudeh, Elsayed, Mariev, and Safonova (2022) showed that green investments are sensitive to geopolitical risk in terms of shock transmission. Wang, Wang, and Chang (2022) demonstrated that green finance positively affects green innovation in emerging countries. At the same time, Tol (2019) showed that national social costs of carbon emissions are the largest in developing countries with large populations, while income convergence raises these costs.

Most econometric methods require precise and granular data that is still unavailable for the most part. In response, the European Banking Authority developed a template for disclosure of the environmental, social and governance (ESG) factors exposure to be used by large banks starting from 2023 (EBA, 2022). At the same time, the European Central Bank (2021) performed ECB economy-wide climate stress tests and climate risk stress tests developed to assess the susceptibility of European banks to climate-change-related shocks (ECB, 2022). Their results show that for many big European banks, the impact of climate risk is very significant and climate change "represents a major source of systemic risk, particularly for banks with portfolios concentrated in certain economic sectors and specific geographical areas" (ECB, 2021, p. 3). The need for developing systemic risk measures that can capture this risk is clear from the results of the cited stress test. The method proposed in this article addresses this need.

### *Controversies around the ESG scores*

ESG ratings have become essential tools for investors, regulators and companies aiming to assess corporate sustainability practices. However, significant inconsistencies across different ESG rating agencies undermine these ratings' utility. These discrepancies stem from several primary sources: methodological differences, variations in definitions and scope, differing aggregation and weighting schemes and the use of disparate data inputs. Consequently, the same firm can receive markedly different ESG assessments depending on the rating provider, complicating stakeholder decision-making and eroding the credibility of ESG metrics overall (Dorfleitner, Kreuzer, & Sparrer, 2020; Billio, Costola, Hristova, Latino, & Pelizzon, 2021).

Mentioned inconsistencies stem largely from differences in the methodologies used by different rating agencies. Each agency employs distinct criteria, weighting schemes and data sources to assess ESG performance. For instance, agencies like Refinitiv (formerly Asset4), Sustainalytics, Bloomberg, MSCI and S&P Global Ratings each have their approach to evaluating ESG factors, which leads to variations in their scoring systems. For example, Refinitiv and Bloomberg focus more on quantitative data related to firm performance, while MSCI and S&P integrate qualitative assessments into their frameworks. These differing methodologies, data sources and scoring philosophies contribute significantly to the lack of alignment observed across ESG ratings (Kotsantonis & Serafeim, 2019; Fiaschi, Giuliani, Nieri, & Salvati, 2020).

A major driver of these inconsistencies is the variation in defining and scoping ESG components. Rating agencies diverge in their conceptualization of what constitutes ESG criteria. Some include a broad array of indicators under each pillar, while others apply narrower, more targeted criteria. Such scope divergence accounts for a substantial portion of the total inconsistency observed in ESG ratings (Dimson, Marsh, & Staunton, 2020; Billio *et al.*, 2021; Berg, Kölbel, & Rigobon, 2022). This lack of standardization complicates the assessment process for investors and other stakeholders seeking to evaluate corporate sustainability performance (Stubbs & Rogers, 2013). Furthermore, Rekker, Humphrey, and O'Brien (2021) argue that current ESG rating approaches often prioritize firm-level materiality and reputational risk management over alignment with broader sustainability goals, such as social equity. This misalignment exacerbates the definitional confusion surrounding ESG and limits the effectiveness of ratings as tools for advancing genuine sustainability transitions.

Discrepancies arising from data sources and quality are closely linked to definitional issues. ESG raters use different data inputs, often collected using proprietary methodologies or from non-uniform reporting sources. This diversity in data origin and reliability significantly contributes to measurement divergence. For instance, research identifies varying data collection approaches as key reasons for inconsistent ESG scores among firms (Widyawati, 2021). Furthermore, using high-quality, standardized data, such as World Bank variables, substantially improves rating consistency (Bouyé & Menville, 2021). However, such data consistency is not always available, particularly at the firm level and even less so across different global markets. The lack of globally harmonized data standards remains a core obstacle to greater convergence in ESG assessments (Billio *et al.*, 2021).

A growing body of research highlights that ESG rating discrepancies are not uniformly distributed across global markets, with emerging economies exhibiting particularly pronounced inconsistencies and regional differences. According to Erhart (2022), firms operating in emerging markets often face higher ESG rating divergence due to limited data availability, inconsistent disclosure practices and selective agency coverage. These challenges are compounded by the fact that many ESG frameworks were originally designed with developed market contexts in mind, resulting in a mismatch when applied globally. Li and Polychronopoulos (2020) further emphasize that the lack of standardized ESG disclosures in emerging markets contributes to rating divergences, suggesting that harmonizing disclosure practices could mitigate inconsistencies.

Moreover, Gibson Brandon, Krueger, and Schmidt (2021) and Avramov, Cheng, Lioui, and Tarelli (2022) highlight that ESG rating disagreements are associated with stock returns, indicating that investors may perceive firms with inconsistent ESG ratings as riskier investments. Furthermore, van Zanten (2025) argues that without greater integration of region-specific ESG risks and institutional dynamics, global ESG ratings risk reinforcing existing information asymmetries and underrepresenting environmental performance in emerging markets. These findings collectively suggest that any assessment of ESG consistency must account for geographic biases, as current rating practices often fail to reflect the nuanced realities of emerging markets.

While ESG rating divergence is an established phenomenon, the degree of inconsistency is not uniform across all pillars. For instance, studies have highlighted that rating divergence is most significant in the governance pillar, where different agencies apply varied governance metrics such as board composition, executive compensation and shareholder rights (Billio *et al.*, 2021; Berg *et al.*, 2022). In contrast, scholars have found that the Environmental component exhibits the least variability among rating providers. Environmental ratings are generally more aligned compared to social or governance scores (Capizzi, Gioia, Giudici, & Tenca, 2021; Dorfleitner, Utz, & Wimmer, 2018). Although some methodological issues persist – such as the use of different environmental metrics and agency-specific weighting in certain industries – these factors tend to influence overall ESG scores more than the consistency of the environmental pillar itself. Agencies commonly assess core indicators such as climate risk management and environmental policy, although they vary somewhat in the specific metrics they use. Moreover, the environmental pillar benefits from somewhat better data availability and comparability, especially when standardized datasets are employed (Billio *et al.*, 2021).

In conclusion, although ESG rating inconsistencies are a well-documented and multifaceted issue, these discrepancies are most significant for the overall scores, less pronounced when the pillar-level scores are compared for different providers, and they are least pronounced in the environmental dimension among the pillars. The environmental scores stand out as relatively more stable and coherent, suggesting that this pillar may serve as a more reliable reference point for stakeholders seeking consistency in ESG evaluations. This makes the environmental dimension particularly suitable for risk assessment analysis.

For these reasons, we chose to focus exclusively on the environmental pillar in this study, selecting a carefully curated sample of institutions that are least impacted by these issues. The environmental pillar is more consistently measured, and so it provides a stable foundation for evaluating the impact of environmental risks. This decision helps limit the controversies and complexities associated with broader ESG assessments.

Furthermore, the methods developed in this study address existing discrepancies by objectivizing the score input. Rather than directly applying the raw ESG scores, we extracted and constructed an environmental factor (e-factor) that reflects environmental risks more accurately. This approach provides a more robust view of the impact of environmental risk on systemic levels, particularly in the context of banks. Robustness analysis confirms that this methodology successfully enhances the accuracy and reliability of the environmental risk assessment, reinforcing the validity of our findings and contributing to a more consistent and actionable approach to environmental risk evaluation.

*Application of ESG scores to risk measurement*

There is extensive research on the ESG factors in the investment-focused frameworks (for reviews, see, e.g. Billio *et al.*, 2021; Gillan, Koch, & Starks, 2021; Berg *et al.*, 2022; Kalia & Gill, 2023). ESG scores are a tool that intends to capture how companies and investors include the ESG aspects in their business (e.g. Scholtens, 2006; Cornett, Erhemjamts, & Tehranian, 2016; Bahadori, Kaymak, & Seraj, 2021; Liu, Shao, De Sisto, & Li, 2021), investment (e.g. Cormier, Ledoux, & Magnan, 2011; Renneboog, Ter Horst, & Zhang, 2011; Bătae, Voicu, & Feleagă, 2020; Wong & Zhang, 2022) and risk management decisions (e.g. Lee & Faff, 2009; Sassen, Hinze, & Hardeck, 2016; Bouslah, Kryzanowski, & M'Zali, 2018; Albuquerque, Koskinen, & Zhang, 2019; Boubaker, Cellier, Manita, & Saeed, 2020; Kim, Lee, & Kang, 2021).

Only a several studies focus on the relationship between ESG factors and banks' risk. Among them, some analyze the role of the ESG factors in risk management, and some describe the potential risk transmission channels (Delis *et al.*, 2021; Finger, Gavious, & Manos, 2018; Gangi, Meles, D'Angelo, & Daniele, 2019; Brunetti *et al.*, 2021; Chiaramonte, Dreassi, Girardone, & Piserà, 2021; Murè, Spallone, Mango, Marzioni, & Bittucci, 2021; Neitzert & Petras, 2021). Various studies link the ESG performance with banking industry assets' quality (Alam *et al.*, 2024; Cantero-Saiz *et al.*, 2024), the shape of the credit portfolios (Abdelsalam *et al.*, 2023), the incidence of losses (Bruno *et al.*, 2024), sustainable liquidity (Gupta & Kashiramka, 2024) and the occurrence of financial distress (Citterio & King, 2023) in banks. In a most recent study, Fioravante, Polato, and Palmieri (2023) found a significant relationship between ESG ratings and borrowers' PD, pointing to a relationship between ESG scores and risk. Other studies focus on the risk in the financial systems (e.g. Anginer, Demirguc-Kunt, & Zhu, 2014, 2018; Cerqueti, Ciciretti, Dalò, & Nicolosi, 2021), and the last few quantify the risk effects of carbon-related and climate risk factors on banks (Delis *et al.*, 2021; Altieri & Radev, 2023; Alam *et al.*, 2024).

In one of the more recent studies, Aevoae *et al.* (2023) investigated the relationship between ESG scores and systemic risk. Based on a sample of 367 banks from 47 countries, they analyze how changes in the scores influence banks' systemic risk contribution using $\Delta$CoVaR (Adrian & Brunnermeier, 2016). Simultaneously, they use SRISK (Brownlees & Engle, 2017) for their robustness checks. Their results indicate a statistically significant relationship between the changes in ESG scores and systemic risk between 2007 and 2020. This relation is robust for financial systems in advanced economies, and it is particularly strong for the environmental factor (Aevoae *et al.*, 2023, p. 4, 16–20). It is one of the two empirical analyses (the first being the aforementioned CRISK model) that uses a large sample of banks, proving that the environmental risk factors significantly influence quantile-based systemic risk measures [2]. Importantly, the study quantifies the size of this impact in an economically meaningful manner.

Despite the plentiful studies discussed in this section, researchers either narrowed the scope of the analysis down to climate risk or kept it distant from the systemic risk analysis itself. We addressed this gap by proposing a solution that allows combining two important nexuses: systemic risk analysis and ESG scoring based on the least controversial environmental pillar.

## Materials and methods

One can take the exposure approach recommended by the European Banking Authority (EBA, 2022) to augment systemic risk analysis with the environmental risk factor. Such an approach assumes using a readily available environmental score as the source of information about bank exposure to environmental risk, which has several advantages going beyond the usage of readily available public data.

Financial Stability Board argues in one of its recommendations on monitoring environmental risks that third-party verification strengthens the reliability of environmental risk data, while relying on external metrics available to authorities and broader financial market participants plays "an important role in avoiding greenwashing risks (FSB, 2022; *Recommendation II*). Moreover, EBA (2021) also indicates that the ESG ratings provided by specialized rating agencies are in the best position to account for not only the risk exposure to ESG factors but also the management's ability to deal with risks and opportunities. This human factor is difficult to systematically quantify in other forms of risk measurement. Moreover, scoring methodologies "build on a quantitative analysis of key issues identified for each industry (and hence company), as well as qualitative information collected by analysts from public information and engagement with companies" (EBA, 2021, p. 75). For these reasons, the exposure approach using the ESG score for systemic risk analysis may be additionally beneficial.

In the baseline empirical analysis, we applied two econometric systemic risk models, i.e. ΔCoVaR and SRISK, to quantify systemic risk, and we added the E-factor extracted from the Environmental score (E-score) using a conditional sensitivity function presented below.

To calculate the daily values of the ΔCoVaR and SRISK for each analyzed bank, we defined the financial system $s$ as a composite of banks $i$ with weights $w_i$ totaling to unity, where $i = 1, \dots, N$, of listed systemically important financial institutions (SIFIs). To identify SIFIs, we used the guidance of the European Banking Authority (2020).

In our modeling approach, $r_{s,t}$ is the rate of return for the financial system $s$ at time $t$ as and for institutions $i$, it is $r_{i,t}$. Value at Risk (VaR) of each financial institution $i$ in the given financial system $s$ at the level of confidence $(1-q)$ equals:

$$VaR_{i,t}^{q}(r_{i,t}) = \inf\left\{r_{i,t} : F_i(r_{i,t}) \geq q\right\}, \tag{1}$$

where $F_i$ is the cumulative distribution function of $r_{i,t}$. Since $\mathbb{P}(r_{i,t} \leq VaR_{i,t}^{q}) = q$, $VaR_{i,t}^{q}$ is determined as a $q$-quantile of the distribution $F_i$, where the VaR of an individual financial institution $i$ equals:

$$VaR_{i,t}^{q} = \sigma_{i,t} F_i^{-1}(q), \tag{2}$$

where $\sigma_{i,t}$ is the volatility of the rates of return at time $t$.

### *ΔCoVaR*

ΔCoVaR is the quantile-based systemic risk measure that captures the contribution of each systemic bank to the overall systemic risk in a non-causal sense. It assumes the conditionality of bank-level risk on the degree of distress of the financial system. However, the focus is on the spillover of risk between banks that makes the financial system more prone to collapse in response to a systemic risk trigger (a shock = financial system distress). Therefore, one may understand ΔCoVaR of a financial institution as its risk spill-over potential. The procedure to calculate ΔCoVaR starts from the financial system perspective and is as follows.

CoVaR of the financial system measures the total price of risk in the financial system that is conditional on an institution being in distress. Formally, $CoVaR_{s,t}$ of the financial system $s$ corresponds to the $VaR_{s,t}^{q}$ of the market return that is obtained conditionally if distress, denoted as $VaR_{i,t}^{q}$ is observed for financial institution $i$. We use the same concept of the financial system and its VaR as for SRISK, as outlined in Equations (1) and (2), but also the $q$ derived as:

$$q = \mathbb{P}\left(r_{s,t} \leq CoVaR_{s,t}^{q|r_{i,t}<VaR_{i,t}^{q}} \middle| r_{i,t} < VaR_{i,t}^{q}\right). \tag{7}$$

$\Delta CoVaR_{i,t}$ captures the marginal contribution of institution $i$ to overall systemic risk in a non-causal sense. The distressed state of financial institution $i$ is defined as $VaR_{i,t}^{q}$, and distress is understood as every instance when losses are at least equal to $VaR_{i,t}^{q}$:

$$\Delta CoVaR_{i,t}^{q} = CoVaR_{s,t}^{q|r_{i,t}<VaR_{i,t}^{q}} - CoVaR_{s,t}^{q|r_{i,t}=Median\left(r_{i,t}\right)}. \tag{8}$$

*SRISK*

SRISK is a systemic risk measure that quantifies the fragility of each financial institution. Like every quantile-based systemic risk measure, it assumes the conditionality of individual bank risk on the state of distress of the financial system. However, the focus is on leverage characteristics that make each bank more prone to collapse in response to a systemic risk trigger (a shock = financial system distress). Therefore, one may understand SRISK of a financial institution as its fragility. The procedure to calculate SRISK is as follows.

The expected Shortfall (ES) of each financial system $s$ is the average of all the losses that are greater than its VaR:

$$ES_{s,t}\left(VaR_{s,t}^{q}\right) = \mathbb{E}_{t-1}\left(r_{s,t} \middle| r_{s,t} < VaR_{s,t}^{q}\right) = \sum_{i=1}^{N} w_{i,t} \cdot \mathbb{E}_{t-1}\left(r_{i,t} \middle| r_{s,t} < VaR_{s,t}^{q}\right). \tag{3}$$

Based on ES, we derive the Marginal Expected Shortfall (MES) for each financial institution $i$ as a partial derivative defined as:

$$MES_{i,t}\left(VaR_{s,t}^{q}\right) = \frac{\partial ES_{s,t}\left(VaR_{s,t}^{q}\right)}{\partial w_{i,t}} = \mathbb{E}_{t-1}\left(r_{i,t} \middle| r_{s,t} < VaR_{s,t}^{q}\right). \tag{4}$$

In turn, the Long-Run Marginal Expected Shortfall (LRMES) of each financial institution $i$ is the expectation that the financial institution's multi-period return on equity is conditional on a systemic event:

$$LRMES_{i,t}\left(VaR_{s,t}^{q}\right) = 1 - \exp\left(-\gamma \cdot MES_{i,t}\left(VaR_{s,t}^{q}\right)\right). \tag{5}$$

where $\gamma$ is the correcting factor relative to the length of the assumed horizon. We assumed that long-run market decline corresponds to a 40% loss over the horizon of six months (cf. Engle & Zazzara, 2018). Assuming the negative definition of risk, we ignored any negative values of SRISK (i.e. any potential capital surpluses). Thus, the SRISK equals:

$$SRISK_{i,t} = \max\{\,0\,;\ \overbrace{k(D_{i,t} + (1 - LRMES_{i,t})V_{i,t})}^{\text{required capital}} - \overbrace{(1 - LRMES_{i,t})V_{i,t}}^{\text{current capital}}\ \}, \tag{6}$$

where $D_{i,t}$ is the value of debt at time $t$, $V_{i,t}$ is the market value of equity at time $t$, and $k$ is the prudential capital fraction. We assumed the $k$ parameter at 8%, which follows Brownlees and Engle (2017), as well as Engle and Zazzara (2018).

*Estimation*

For the sake of comparability and coherence of empirical application to different systemic risk measures, we applied the same estimation procedures to all systemic risk measures, estimating model parameters following the literature (Brownlees & Engle, 2017, 2017; Benoit *et al.*, 2017). To model conditional volatility, we used the GJR-GARCH approach, and to model dynamic correlation, we used the GARCH-DCC (cf. *V-Lab Documentation* [3]), in which $r_t$ is the vector of $(r_{s,t}, r_{i,t})$ at time $t$, and $r_t$ is the conditional variance-covariance matrix at time $t$:

$$r_t = \sqrt{\mathbf{C}_t}\upsilon_t. \tag{7}$$

The vector $\upsilon_t$ of independent and identically distributed random variables $(\varepsilon_{s,t}, \varepsilon_{i,t})$ is such that $\mathbb{E}(\upsilon_t) = 0$ and $\mathbb{E}(\upsilon_t \upsilon_t') = \mathbb{I}_2$ is a 2×2 unit matrix. The matrix takes the form of:

$$\mathbf{C}_t = \begin{pmatrix} \sigma_{s,t}^2 & \sigma_{i,t}\sigma_{s,t}\rho_{s,i,t} \\ \sigma_{i,t}\sigma_{s,t}\rho_{s,i,t} & \sigma_{i,t}^2 \end{pmatrix}, \tag{8}$$

where $\sigma_{s,t}$ is the conditional standard deviation of the system $s$ at time $t$, $\sigma_{i,t}$ is the conditional standard deviation of the financial institution $i$ at time $t$, and $\rho_{s,i,t}$ is the time-varying conditional correlation coefficient. The MES estimator equals:

$$\widehat{MES}_{i,t}\left(VaR_{s,t}^q\right) = \widehat{\sigma}_{i,t}\widehat{\rho}_{i,t}\widehat{\mathbb{E}}_{t-1}(\varepsilon_{s,t}|\varepsilon_{s,t} < \kappa_t) + \widehat{\sigma}_{i,t}\sqrt{1 - \widehat{\rho}_{i,t}^2}\,\widehat{\mathbb{E}}_{t-1}(\varepsilon_{i,t}|\varepsilon_{s,t} < \kappa_t). \tag{9}$$

For $\kappa_t = \frac{VaR_{s,t}^q}{\sigma_{s,t}}$, $K(x) = \int_{-\infty}^{\frac{x}{h}} k(u)du$, where $k(u)$ is a normal distribution density function and $h = T^{\frac{-1}{5}}$, we assumed:

$$\widehat{\mathbb{E}}_{t-1}(\varepsilon_{s,t}|\varepsilon_{s,t} < \kappa_t) = \frac{\sum_{\tau=1}^{T} K\left(\frac{\kappa_t - \varepsilon_{s,\tau}}{h}\right)\varepsilon_{s,\tau}}{\sum_{\tau=1}^{T} K\left(\frac{\kappa_t - \varepsilon_{s,\tau}}{h}\right)} \tag{10}$$

and

$$\widehat{\mathbb{E}}_{t-1}(\varepsilon_{i,t}|\varepsilon_{s,t} < \kappa_t) = \frac{\sum_{\tau=1}^{T} K\left(\frac{\kappa_t - \varepsilon_{s,\tau}}{h}\right)\varepsilon_{i,\tau}}{\sum_{\tau=1}^{T} K\left(\frac{\kappa_t - \varepsilon_{s,\tau}}{h}\right)}. \tag{11}$$

Then we estimated the long-run MES as:

$$\widehat{LRMES}_{i,t}\left(VaR_{s,t}^q\right) \approx 1 - \exp\left(-18 \cdot \widehat{MES}_{i,t}\left(VaR_{s,t}^q\right)\right). \tag{12}$$

and SRISK as:

$$\widehat{SRISK}_{i,t} = \max\{0\,;\ \overbrace{k(D_{i,t} + (1 - \widehat{LRMES}_{i,t})V_{i,t})}^{\text{required capital}} - \overbrace{(1 - \widehat{LRMES}_{i,t})V_{i,t}}^{\text{current capital}}\}. \tag{13}$$

For empirical calculations, we used the SRISK measure expressed as a percentage of market capitalization.

Simultaneously, we estimated ΔCoVaR in accordance with the formula:

$$\Delta \widehat{CoVaR}^{q}_{i,t} = \rho_i \sigma_s \widehat{VaR}^{q}_{s,t}, \tag{14}$$

where we insert the VaR of the financial system calculated based on the weighted average of returns of listed systemically important financial institutions used to create the financial system model (see equations (1) and (2)).

### *Augmenting for the environmental factor*

The augmentation of the systemic risk measures with the E-factor is based on rescaling, whereby a lower environmental pillar score leads to a greater increase in the value of a systemic risk measure. To model this relationship, we synchronize the frequency of the given systemic risk measure (SRISK or ΔCoVaR) and the E-score series quotations by assigning the annual environmental quotation to the middle business day (the earlier of both, if two) of the following year. Then we extend the obtained quotations to all business days using piecewise linear interpolation. We maintain the last available annual quotation for all subsequent working days until the end of the considered data sample.

To standardize the time ends of all the analyzed series, we introduce a lag into the E-score series while leaving a constant value that repeats the last quote until the end of the analyzed period. By doing so, we assume that all stakeholders, including the analyzed bank and its investors, utilize the last known information regarding the E-score in their investment and risk-management decisions. Hence, the last known E-score has an impact until new information becomes available. The findings of behavioral finance theory motivated this approach (Kahneman, 2013).

More specifically, behavioral finance research suggests that relying on the most recent available information is not just common but also a rational response to uncertainty under prospect theory (Kahneman & Tversky, 1979; Barberis & Thaler, 2003). In the absence of more up-to-date data, all stakeholders, including banks and investors, naturally anchor their decisions to the last known E-score, ensuring that investment and risk-management strategies remain informed by the best available evidence. This aligns with the well-documented recency effect (Daniel, Hirshleifer, & Subrahmanyam, 1998), which allows decision-makers to quickly adapt to new information once it becomes available. Such behavior enhances market efficiency by preventing overreaction to incomplete signals (Shiller, 2014) and providing a stable basis for systemic risk assessments (Shefrin, 2007). This underscores the importance of timely environmental risk disclosures while recognizing that investors' reliance on the latest data is a practical and strategic choice.

To augment systemic risk measurement with the described E-factor, we follow the equation, where we define the E-SRISK as:

$$E\_SRISK_{i,t} = SRISK_{i,t}(1 + \beta(100 - E_{i,t})) \tag{15}$$

and E-ΔCoVaR as:

$$E\_\Delta CoVaR_{i,t} = \Delta CoVaR_{i,t}(1 + \beta(100 - E_{i,t})) \tag{16}$$

In the equation above, $E_{i,t}$ represents the E-factor based on the E-score. They all relate to a bank $i$ on a business day $t$.

Algebraic operations allow for rewriting equations (15) and (16) as:

$$E\_SRISK_{i,t} = SRISK_{i,t} + \beta(100 - E_{i,t})SRISK_{i,t}, \tag{17}$$

$$E\_\Delta CoVaR_{i,t} = \Delta CoVaR_{i,t} + \beta(100 - E_{i,t})\Delta CoVaR_{i,t}, \tag{18}$$

Equations (17) and (18) demonstrate that the increase in the augmented systemic risk measure is proportional to the decrease in the E-factor, while the scale of this change depends on its current level – the higher the current level of SRISK or ΔCoVaR, the stronger the impact. Moreover, if the systemic risk measure decays to zero, the influence of the E-factor on it disappears. In other words, low levels of the E-score increase systemic risk, and the higher the E-score (the better the environmental score of a given bank) – the smaller the effect of this score on systemic risk. This property of the E-factor is in line with the recent findings of the ECB (2022) and the EBA's recommendations (2022).

The $\beta$ coefficient may take the form of a function of time, i.e. $\beta = \beta(t)$. Such an approach makes it possible to introduce the perception of the time-varying significance level of the environmental factor as a risk factor for an institution, postulated in the literature on the subject and could account for the increased impact of the E-factor on systemic risk in the following years, as suggested by the ECB's stress tests (2021, 2022) – for the horizon of the year 2050.

The proposed model has one other important characteristic: it allows the creation of beta-independent rankings. To illustrate this mathematically, let $\mathcal{T}$ be the set of days from a fixed time horizon. Then the surplus area for a given institution/bank for E-SRISK is calculated as:

$$S\_SURP_i(\mathcal{T}) = \frac{\sum_{t\in\mathcal{T}} E\_SRISK_{i,t}}{\sum_{t\in\mathcal{T}} SRISK_{i,t}} - 1 = \frac{\sum_{t\in\mathcal{T}} \beta(100 - E_{i,t})SRISK_{i,t}}{\sum_{t\in\mathcal{T}} SRISK_{i,t}}, \tag{19}$$

and for ΔCoVaR as:

$$C\_SURP_i(\mathcal{T}) = \frac{\sum_{t\in\mathcal{T}} E\_\Delta CoVaR_{i,t}}{\sum_{t\in\mathcal{T}} \Delta CoVaR_{i,t}} - 1 = \frac{\sum_{t\in\mathcal{T}} \beta(100 - E_{i,t})\Delta CoVaR_{i,t}}{\sum_{t\in\mathcal{T}} \Delta CoVaR_{i,t}}. \tag{20}$$

Since Formulas (17) and (18) hold, it yields that:

$$S\_SURP_i(\mathcal{T}) = \beta\cdot\frac{\sum_{t\in\mathcal{T}} (100 - E_{i,t})SRISK_{i,t}}{\sum_{t\in\mathcal{T}} SRISK_{i,t}} \text{ and } C\_SURP_i(\mathcal{T}) = \beta\cdot\frac{\sum_{t\in\mathcal{T}} (100 - E_{i,t})\Delta CoVaR_{i,t}}{\sum_{t\in\mathcal{T}} \Delta CoVaR_{i,t}} \tag{21}$$

meaning that $\beta = \beta(t) = \beta_{i,t}$ that is constant in time and the same for all financial institutions.

In this case, the rankings created based on surplus will not depend on the choice of the coefficient value. We used this feature of our model in the following empirical section.

In this study, we augmented two measures: SRISK and ΔCoVaR. However, the proposed method applied to any other systemic risk measure for which one can prove a significant relationship between the E-score and systemic risk levels. Furthermore, even though we used the ESG scores provided by the Thomson Reuters Refinitiv database, the presented method allows for extracting the E-factor from any existing environmental score [4].

### *Data*

Based on the publicly available data, we quantified E-SRISK and E-ΔCoVaR – systemic risk augmented with the E-factor for a versatile group of 20 banks from 12 different European countries (both advanced and emerging economies), including Austria, Belgium, France, Germany, Greece, Hungary, Italy, the Netherlands, Poland, Romania, Russia and Sweden.

The selection of the 20 banks in this study was deliberate rather than random, ensuring an illustrative sample that accounts for data constraints and enhances contrasts between Western and Central and Eastern European (CEE) banks. Given the uneven data availability, particularly the deficit in the East, we used a purposive approach to create a more balanced data set. From the 68 banks initially considered, we selected a diverse subset, including "borderline" institutions in the ranking, to highlight variations in banking structures and performance across regions. Rather than providing a comprehensive application of the method, this study illustrates its analytical utility through carefully selected cases. We chose banks that are well-known institutions, picked to emphasize regional contrasts while maintaining conciseness and avoiding results dilution but also selected based on the data availability and completeness. The potential impact of the Single Supervisory Mechanism (SSM) served as an additional selection criterion to enhance completeness and representativeness. To this end, we deliberately included 10 banks under SSM supervision and 10 banks outside its scope. This targeted selection strengthens the findings' clarity and results' robustness.

Despite a moderate number of banks, the empirical data set encompassing the period from 2007 to 2023 included a large number of approximately 88,500 observations regarding the analyzed banks' stock prices and market cap each and approx. 3,100 book value entries. The data set covered all available entries on the ESG scores in the sampled period (488 entries), from which we extracted the E-factor based on the Environmental score (hereafter E-score). This gave a total of about 180,000 data entries. Appendix contains the relevant descriptive statistics, as well as the list of the analyzed banks and indices. The sources of data used in this study include Refinitiv, for stock prices and baseline ESG scores and Bloomberg for alternative ESG scores used in robustness exercises.

The baseline main study E-score is part of the ESG Score calculated according to Refinitiv (2025) methodology based on three pillars: emissions, innovation and resource use. The score is set differently for different industries since different pro-ecological behaviors and solutions can have a bigger impact on the environment in different sectors. At the same time, the concept of climate change remains in focus here. For the banking sector, Refinitiv uses 22 datapoints per bank yearly, while the weights of the mentioned three pillars are 0.17 for emissions, 0.67 for green innovation and 0.17 for resource use, respectively. Thus, the score is a reasonably comprehensive measure that uses all available data for the final E-score computation while adjusting for its significance through the weighting process.

Refinitiv's ESG scoring methodology is more dynamic in comparison with alternative scoring frameworks and includes several incentivizing mechanisms. For instance, the 2020 methodology introduced a materiality matrix that weights ESG factors according to industry relevance, a transparency incentive where companies not disclosing key data are penalized with zero scores, and an adjustment to reduce company size bias in controversy assessments. In contrast, the current methodology, reflected in the 2023 update of the Refinitiv ESG dataset, further enhanced data quality by introducing granularity, improved normalization techniques and a streamlined metric set to increase consistency and comparability. The newer approach also places greater emphasis on real-time updates and integration with AI-driven data collection, improving timeliness and accuracy. Overall, while the 2020 changes laid the groundwork for a more robust ESG framework, the latest methodology offers increased precision and adaptability to the rapidly evolving ESG landscape.

## Model application to empirical data

### *Environmental risk-based rankings*

The following section illustrates how the model works on actual empirical data. In the study presented here, we assumed $q = 1\%$ and the value of $\beta = 0.95\%$, which was in line with the findings of the two most recent empirical studies, both of which come to a very similar conclusion regarding the size of the systemic impact of the environmental factor (cf. Aevoae *et al.*, 2023; Eratalay & Cortés Ángel, 2022). They are also in line with the recent stress test of the European Central Bank (2021) as to the magnitude of the modeled effect. However, the rankings generated with our method are beta-independent and remain unchanged regardless of the beta-value setting. The value of beta only affects the illustration in the form of the graphs presented in Appendix. The mentioned graphs present the results obtained for each analyzed bank, where the black time series represents the time-varying values of the baseline measures: ΔCoVaR and SRISK and the colored lines indicate the values of systemic risk measures augmented with the two alternative E-factors.

Figures A1 to A80 in Appendix illustrate the results. Generally speaking, we observed that the impact of the E-factor was bigger in the periods of instability (around the peaks) that relate to various significant systemic risk triggers, such as the global financial crisis, the European public debt crisis, the recent COVID-19 pandemic and the war onset. We also noticed that the E-factor had a higher impact on systemic risk, the higher the general level of systemic risk of a given bank was. This observation is valid for all systemic risk measures and for banks from developed and emerging countries similarly. It is also relevant for all banks, regardless of whether they are global SIFIs or not (cf. Table A1 in Appendix).

We also found an evident geographic variability. We can distinguish banks characterized by high E-scores throughout the study period. They include Italian, French, German, Belgian and Dutch banks, which brand themselves as pro-environmental and sustainable, such as Société Générale S.A. (France), Commerzbank AG and Deutsche Bank AG (Germany) or UniCredit S.p.A. and Intesa San Paolo S.p.A. (Italy). On the opposite side of the spectrum, there are several systemic banks from Central Europe, including two Romanian banks (Banca Transilvania SA and BRD Bank), two Polish banks (PKO BP SA and mBank SA), two Russian banks (Sberbank and VTB PAO) and one Western European bank that has a substantial presence in the CEE region – Raiffeisen Bank International AG. Very high E-score surpluses of around 40%–60% estimated for these banks point to severe environmental systemic risk exposures.

To quantify the impact of the E-factor on SRISK and ΔCoVaR in a more interpretable and meaningful manner, we constructed a set of beta-independent rankings for the analyzed banks. We based these rankings on the ratio of the area enclosed between the E-augmented and baseline time series to the area under the baseline systemic risk measure over time, assuming a continuous time framework. This ratio, expressed as a percentage, captures the average surplus of E-SRISK relative to baseline SRISK and E-ΔCoVaR relative to baseline ΔCoVaR. In other words, it reflects the average increase in risk attributable to the inclusion of the environmental factor.

To estimate the required areas, we used the sum of the values within each time series. We determined the time range considered for each bank individually, based on the availability of the necessary data. Using this relative measure – a surplus per fixed unit of time – helps to mitigate the bias introduced by differences in time span across banks due to data limitations. The resulting rankings are robust across multiple re-estimations of the underlying GARCH models and hold consistently across various sub-periods. Tables 1 and 2 present the final rankings for the entire period under analysis, based on E-ΔCoVaR and E-SRISK, respectively.

For the most part, both rankings robustly confirmed the same characteristics, placing the banks from developed Western European countries at the top of the ranking, the two Swedish banks in the middle, and the CEE region on the lower side of the table. We observed only mild differences. Only two banks out of the 20 banks covered by both rankings interchanged their position when the two rankings were concerned relative to the first ranking. These banks were KBC Group N.V. (Belgium) and UniCredit S.p.A. (Italy) – but the difference in their surpluses was very small – about 0.16% and 0.07%, respectively. In all other cases, the ranking stayed the same, despite applying a completely different risk measure.

Notably, the two systemic risk measures applied in Tables 1 and 2 have a different nature – one focuses on spillover effects, the other on fragility. The literature shows that at the central point, systemic risk measures are not highly correlated; they become ubiquitous in the tails of the distribution. Hence, variability in the central part of the ranking is expected. All in all, the analysis indicates a particularly strong robustness of the results. This robustness was further confirmed for two alternative systemic risk measures applied in robustness analysis (see

**Table 1.** Ranking of banks based on the surplus of the E-ΔCoVaR over ΔCoVaR: the whole analyzed period

| Bank | Country | Total surplus |
|---|---|---|
| Intesa San Paolo S.p.A | Italy | 6.62% |
| Société Générale S.A. | France | 6.63% |
| Deutsche Bank A.G. | Germany | 7.96% |
| Commerzbank A.G. | Germany | 9.78% |
| KBC Group N.V. | Brussels | 10.77% |
| UniCredit S.p.A | Italy | 10.93% |
| ING Bank N.V. | The Netherlands | 11.15% |
| Skandinaviska Enskilda Banken A.B. | Sweden | 11.73% |
| Swedbank A.B. | Sweden | 16.13% |
| Erste Group Bank A.G. | Austria | 22.28% |
| Eurobank E.S.&H. S.A. | Greece | 25.22% |
| OTP Bank Nyrt | Hungary | 27.63% |
| Raiffeisen Bank IA.G. | Austria | 37.08% |
| ING Bank Śląski S.A. | Poland | 39.84% |
| BRD – Groupe Société Générale S.A. | Romania | 41.08% |
| VTB PA.O. | Russia | 44.04% |
| mBank S.A. | Poland | 44.37% |
| Banca Transilvania S.A. | Romania | 47.36% |
| Sberbank PA.O. | Russia | 58.45% |
| Powszechna Kasa Oszczędności Bank Polski S.A. | Poland | 61.12% |

**Source(s):** Own elaboration

**Table 2.** Ranking of banks based on the surplus of the E-SRISK over SRISK: the whole analyzed period (robustness)

| Bank | Country | Total surplus |
|---|---|---|
| Société Générale S.A. | France | 5.85% |
| Intesa San Paolo S.p.A | Italy | 6.51% |
| Deutsche Bank A.G. | Germany | 7.66% |
| Commerzbank A.G. | Germany | 9.28% |
| UniCredit S.p.A | Italy | 10.80% |
| KBC Group N.V. | Brussels | 10.87% |
| ING Bank N.V. | The Netherlands | 11.11% |
| Skandinaviska Enskilda Banken A.B. | Sweden | 11.77% |
| Swedbank A.B. | Sweden | 16.04% |
| Erste Group Bank A.G. | Austria | 20.77% |
| Eurobank E.S.&H. S.A. | Greece | 25.98% |
| OTP Bank Nyrt | Hungary | 26.68% |
| Raiffeisen Bank IA.G. | Austria | 30.91% |
| ING Bank Śląski S.A. | Poland | 39.94% |
| BRD – Groupe Société Générale S.A. | Romania | 40.14% |
| VTB PA.O. | Russia | 43.46% |
| mBank S.A. | Poland | 44.54% |
| Banca Transilvania S.A. | Romania | 45.15% |
| Sberbank PA.O. | Russia | 56.04% |
| Powszechna Kasa Oszczędności Bank Polski S.A. | Poland | 59.42% |

**Source(s):** Own elaboration

Section 4.4), where each additional measure applied was the equivalent of each of the two systemic risk measures applied in the main study.

To further investigate the robustness of the models, we constructed eight additional rankings, one for each systemic risk measure in each sub-period characterized by different systemic turbulence: the period of the global financial crisis (2007–2009), the period of the public debt crisis in Europe (2010–2013), the period of prolonged low interest rates and economic stagnation (2014–2019), the COVID-19 pandemic (January 2020–December 2021) and the war-induced turbulence (2022–2023). Tables 3 and 4 present the results.

Table 3 captures several differences between the sub-periods, with a general trend towards E-factor exposure reduction over time. Still, individual banks have different characteristics. Such banks as ING (Netherlands and Poland) significantly reduced their environmental risk exposure gradually in the whole period, regardless of external turbulence, while other banks moved in the opposite direction in the past turbulent periods (e.g., PKO BP or mBank in Poland) or the pandemic (e.g., Raiffeisen, Austria). One Russian bank (VTB) showed an increase in environmental risk exposure over time. We may draw similar conclusions from the ranking presented in Table 4.

As in the previous case, rankings based on E-ΔCoVaR and E-SRISK have a lot in common. Western banks are positioned mostly at the top of the rankings and Central European ones – at the bottom. For the majority of banks, the environmental exposure diminished over time, for the same few banks as before – the trend was reversed, or there was no clear trend with the exposure swinging back and forth. Moreover, rankings based on both measures point to an unexpected observation in relation to Raiffeisen Bank and the Romanian banks one year after they started to be graded by the E-score. We observed similar – somewhat smaller – one-off effects also for two Polish banks (mBank and ING Bank Śląski) in the same sub-periods.

**Table 3.** Ranking of banks based on the surplus of the E-ΔCoVaR over ΔCoVaR: Subperiods

| Bank | Country | 2007–2009 | 2010–2013 | 2014–2019 | 2020–2021 | 2022–2023 |
|---|---|---|---|---|---|---|
| Intesa San Paolo S.p.A | Italy | 9.01% | 6.50% | 7.33% | 5.27% | 2.17% |
| Société Générale S.A. | France | 12.63% | 5.14% | 5.57% | 4.90% | 3.40% |
| Deutsche Bank A.G. | Germany | 13.61% | 9.50% | 4.54% | 5.05% | 7.36% |
| Commerzbank A.G. | Germany | 9.72% | 8.05% | 12.46% | 8.87% | 6.75% |
| KBC Group N.V. | Brussels | 11.08% | 11.65% | 11.59% | 8.95% | 7.50% |
| UniCredit S.p.A | Italy | 11.87% | 10.45% | 12.23% | 9.54% | 8.01% |
| ING Bank N.V. | The Netherlands | 12.05% | 11.97% | 9.82% | 13.33% | 7.10% |
| Skandinaviska Enskilda Banken A.B. | Sweden | 15.24% | 11.96% | 9.87% | 8.68% | 10.86% |
| Swedbank A.B. | Sweden | 23.83% | 14.61% | 13.56% | 15.65% | 7.63% |
| Erste Group Bank A.G. | Austria | 36.81% | 19.28% | 17.54% | 18.18% | 12.21% |
| Eurobank E.S.&H. S.A. | Greece | 27.88% | 27.84% | 22.57% | 31.93% | 15.07% |
| OTP Bank Nyrt | Hungary | 35.14% | 32.03% | 27.50% | 22.54% | 12.31% |
| Raiffeisen Bank IA.G. | Austria | 64.02% | 34.05% | 24.52% | 31.51% | 20.01% |
| ING Bank Śląski S.A. | Poland | 73.80% | 70.06% | 36.13% | 11.24% | 4.80% |
| BRD – Groupe Société Générale S.A. | Romania |  |  | 60.48% | 35.43% | 19.07% |
| VTB PAO | Russia | 55.17% | 41.05% | 39.45% | 45.47% |  |
| mBank S.A. | Poland |  | 52.96% | 65.40% | 23.07% | 11.41% |
| Banca Transilvania S.A. | Romania |  |  | 84.99% | 23.65% | 17.60% |
| Sberbank PA.O. | Russia | 77.96% | 57.08% | 55.07% | 37.60% |  |
| Powszechna Kasa Oszczędności Bank Polski S.A. | Poland | 77.98% | 79.43% | 65.17% | 42.64% | 22.10% |

**Source(s):** Own elaboration

**Table 4.** Ranking of banks based on the surplus of the E-SRISK over SRISK: subperiods

| Bank | Country | 2007–2009 | 2010–2013 | 2014–2019 | 2020–2021 | 2022–2023 |
|---|---|---|---|---|---|---|
| Société Générale S.A. | France | 12.32% | 5.27% | 5.49% | 5.07% | 3.40% |
| Intesa San Paolo S.p.A | Italy | 9.29% | 6.51% | 7.83% | 4.63% | 2.20% |
| Deutsche Bank A.G. | Germany | 13.76% | 9.50% | 4.44% | 5.05% | 7.19% |
| Commerzbank A.G. | Germany | 8.63% | 7.96% | 12.46% | 8.71% | 6.81% |
| UniCredit S.p.A | Italy | 11.95% | 10.39% | 12.49% | 8.79% | 8.06% |
| KBC Group N.V. | Brussels | 11.36% | 11.66% | 11.38% | 8.94% | 7.42% |
| ING Bank N.V. | The Netherlands | 12.25% | 11.83% | 10.04% | 13.15% | 7.18% |
| Skandinaviska Enskilda Banken A.B. | Sweden | 15.23% | 12.03% | 9.91% | 8.79% | 10.93% |
| Swedbank A.B. | Sweden | 23.55% | 14.69% | 13.73% | 15.38% | 7.67% |
| Erste Group Bank A.G. | Austria | 36.64% | 18.88% | 17.54% | 18.18% | 12.19% |
| Eurobank E.S.&H. S.A. | Greece | 27.98% | 27.62% | 23.10% | 31.58% | 15.29% |
| OTP Bank Nyrt | Hungary | 35.15% | 31.54% | 27.46% | 22.02% | 12.58% |
| Raiffeisen Bank IA.G. | Austria | 64.36% | 32.33% | 24.23% | 30.99% | 20.29% |
| ING Bank Śląski S.A. | Poland | 73.80% | 69.66% | 34.60% | 11.15% | 4.65% |
| BRD – Groupe Société Générale S.A. | Romania | | | 60.50% | 32.12% | 19.50% |
| VTB PA.O. | Russia | 55.23% | 40.75% | 41.37% | 45.56% | |
| mBank S.A. | Poland | | 55.14% | 63.57% | 22.98% | 11.36% |
| Banca Transilvania S.A. | Romania | | | 83.47% | 21.78% | 17.84% |
| Sberbank PA.O. | Russia | 78.01% | 56.16% | 54.75% | 36.93% | |
| Powszechna Kasa Oszczędności Bank Polski S.A. | Poland | 78.01% | 79.53% | 64.54% | 41.97% | 21.76% |

**Source(s):** Own elaboration

The sudden one-off drops of the E-factor that correspond to high increases in the E-score suggest there might be a case of the green-washing effect, and thus, they should be treated with caution. Robustness analysis with the application of two additional systemic risk measures further confirmed these results (Section 4.4).

The differences in ranks between the E-ΔCoVaR and E-SRISK rankings correspond to the ones indicated in Tables 1 and 2 presented earlier. However, we see that the shifts in the sub-periods correspond to spikes in systemic risk that were institution-specific and crisis-specific. For instance, for the Greek Eurobank – they correspond to the public debt crisis, while for the German Commerzbank – to the collapse of Lehman Brothers. Such differences agree with the different natures of the two analyzed systemic risk measures. As SRISK (like QLaR) is a measure of bank fragility – a characteristic that builds up over a longer period and is more spread across the time axis, the impact of the E-factor is also more spread across time here. On the other hand, ΔCoVaR [like Dynamic Systemic Risk Index (DSRI)] is a more dynamic measure characterized by steeper slopes and higher peaks that relate to more sudden reactions to shocks and their subsequent propagation to the system. This characteristic allowed the second-ranking to capture the short-lived systemic risk spikes in the changing ranks of these banks that were exposed to particularly strong shocks in different sub-periods. All results were firmly robust across different sub-periods and systemic risk measures, as indicated by significantly high-rank correlation coefficients presented in Section 4.4.

We found that environmental risks are more pronounced in the CEE region compared to Western Europe, using the SRISK framework to assess systemic risk across 12 European countries (7 from Western Europe and 5 from CEE). These results are broadly consistent with recent CEE-focused studies. For instance, Ritter (2022) found that over 60% of Hungarian banking sector exposures were significantly affected by transition risks, while Kosztowniak and Kozak (2023) reported that 51% of Poland's banking sector was exposed to high-carbon or "dirty" assets. Várgedő (2022) observed similar comparable vulnerabilities within Hungary's banking system. Although these studies employed different methodologies, the alignment in outcomes reinforces the relevance of environmental risk in the region.

In contrast to approaches that estimate credit risk outcomes under specific climate policy scenarios, such as Nehrebecka (2021), who projected PD increases of up to 10.12% under carbon tax assumptions in Poland, our framework integrates environmental risk indicators directly into a systemic risk framework. This allows for a more structural perspective on how climate-related exposures may translate into broader financial system vulnerabilities.

The methodological basis of our work also differs from earlier European studies. Battiston, Mandel, Monasterolo, Schütze, and Visentin (2017) implemented a network-based climate stress test across Euro Area financial institutions and identified substantial exposures of equity portfolios to climate-related risks. Similarly, Dunz *et al.* (2021) conducted a macro-level climate stress test to assess financial stability impacts across sectors. While the techniques vary, the results generally converge, suggesting that banks and economies with higher carbon footprints face elevated risk levels.

While our study does not match the geographic breadth of Afzal, Hasnaoui, Firdousi, and Noor (2024), who investigated green banking practices in 27 European countries and their effects on profitability and credit risk, it contributes a distinct comparative perspective by contrasting systemic environmental risks across two European subregions. The higher risk levels observed in CEE countries add a useful regional lens to ongoing discussions about climate finance and financial stability, particularly in the context of banking sector exposure to environmental transition dynamics.

### *SSM mechanism*

The SSM is the framework for banking supervision within the euro area, established as one of the pillars of the European Banking Union. It was formally created in November 2014 and is operated by the ECB in cooperation with the national supervisory authorities of participating EU countries. The primary objective of the SSM is to ensure the safety and soundness of the European banking system, increase financial integration and stability and foster consistent supervision across the euro area. Under this framework, the ECB directly supervises significant institutions, while less significant institutions remain under national supervision but within a harmonized regulatory environment.

The SSM offers several key advantages for financial stability. It provides uniform supervisory standards across the euro area, promotes timely identification and mitigation of systemic risk and reduces the potential for regulatory arbitrage. By centralizing supervision of large cross-border banking groups, the SSM enhances transparency and coordination, particularly important in times of financial distress.

In the context of this study, 10 of the 20 banks analyzed have been subject to direct supervision under the SSM since 2014/15, while the remaining 10 have operated outside this framework. The banks under SSM supervision include the banks from Austria, Belgium, France, Germany, Greece, Italy and the Netherlands, while the banks from Sweden and the CEE region are not directly a part of the SSM.

This divergence in supervisory regimes could have meaningful implications for ESG performance, particularly in the environmental domain. However, our findings suggest that the effect of SSM membership is not as pronounced as one might intuitively expect. While SSM-supervised banks generally demonstrate more extensive environmental disclosures, this appears to affect the quantity but not necessarily the quality of environmental risk management practices or outcomes.

A more influential factor in explaining the variance in environmental scores appears to be the geographic distribution and regional characteristics of the banks. In particular, banks headquartered in CEE tend to exhibit worse environmental performance metrics compared to their Western European counterparts. This observation correlates strongly with regional differences in air pollution levels, industrial emissions and the dominance of carbon-intensive energy models, such as reliance on coal and brown fuels for electricity and heating. Moreover, the economic structure in CEE countries often involves greater financial exposure to industries associated with high environmental externalities, such as mining, coal extraction and heavy manufacturing.

Specific cases further substantiate this geographic link. For instance, Swedish banks such as Swedbank and SEB, while not part of the SSM, nonetheless exhibit high environmental scores, reflecting Sweden's comparatively low emissions and progressive environmental policy landscape. Conversely, Raiffeisen Bank International, headquartered in Austria and under SSM supervision since 2014, shows relatively poor environmental scores, partially driven by its exposure to high-emission sectors and also by a previously documented case of alleged greenwashing, which temporarily distorted its reported ESG metrics.

Taken together, these observations underscore that while SSM supervision enhances transparency, it does not uniformly translate into superior environmental performance. Regional environmental conditions and structural economic dependencies appear to play a more decisive role. Nonetheless, the increased environmental reporting observed among SSM-supervised banks may support better future alignment with environmental standards as regulatory expectations evolve.

This is in line with earlier literature findings. Other studies suggest that existing regulatory frameworks may not be fully effective in addressing climate-related financial risks in the CEE region. While studies like Kosztowniak and Kozak (2023) point to a growing share of green exposures in Poland – possibly reflecting the influence of regulatory incentives – the overall preparedness remains uneven. Chabot, Bertrand, and Courquin (2023) emphasize the need for mandatory climate risk assessment and disclosure, indicating that regulatory systems across both Western and CEE Europe may lack the necessary scope or enforcement. These and our findings highlight that differences in regulation, its implementation and incentives contribute to the varying levels of climate risk exposure observed between regions.

### *Robustness analysis*

To validate the consistency and reliability of our results, we conducted a three-pronged robustness analysis. We designed each step to examine the sensitivity of the E-factor-based time series and rankings to alternative scoring inputs and systemic risk measures, as well as to confirm the distinct informational value of our methodology.

First, we assessed whether the E-factor-based rankings offer added value compared to rankings derived directly from ESG environmental scores. Specifically, we constructed bank rankings based solely on the environmental pillar scores provided by Refinitiv (see Appendix) and compared them with those generated through our E-factor methodology. Table 5 illustrates significant differences between the rankings.

**Table 5.** Differences between E-score and E-factor-based rankings

| | 2007–2009 | 2010–2013 | 2014–2019 | 2020–2021 | 2022–2023 | 2007–2023 |
|---|---|---|---|---|---|---|
| number of banks | 17 | 18 | 20 | 20 | 18 | 20 |
| E-ΔCoVaR difference | 7 (41%) | 6 (33%) | 7 (35%) | 12 (60%) | 13 (72%) | 8 (40%) |
| E-SRISK difference | 9 (53%) | 7 (39%) | 2 (10%) | 9 (45%) | 13 (72%) | 5 (25%) |
| E-DSRI difference | 7 (41%) | 7 (39%) | 6 (30%) | 12 (60%) | 13 (72%) | 6 (30%) |
| E-QLaR difference | 9 (53%) | 7 (39%) | 4 (20%) | 8 (40%) | 13 (72%) | 9 (45%) |
| Average difference | *8 (47%)* | *6.75 (38%)* | *4.75 (24%)* | *10.25 (51%)* | *13 (72%)* | *7 (35%)* |

**Source(s):** Own elaboration

Table 5 presents the comparative results and confirms that the E-factor rankings significantly diverge from those based on raw E-scores. We observed the largest concordance during the calmest period, 2014–2019. Simultaneously, the differences were more prominent during turbulent periods – the global financial crisis, the COVID-19 pandemic and the Ukrainian war – similarly for all systemic risk measures applied. This finding especially strongly underscores that our approach captures differentiated and dynamic aspects of environmental risk that are not fully embedded in static ESG scoring frameworks.

While the results confirmed that over the longer periods, the environmental risk factors had a similar impact on banks' fragility and on their ability to propagate shocks, the ESG scores were not effective in capturing the systemic-risk-induced environmental risk triggers. Our observations confirmed that integrating the E-score into bank-specific systemic risk measures, such as SRISK or ΔCoVaR, captures an essential characteristic: environmental risk exposures can increase the losses incurred in crises more than in the calm periods, even if the risk factors themselves are not directly related to the crisis at hand. Thus, E-factor augmentation helps to improve systemic risk measurement in a meaningful way.

Next, we tested the findings' robustness against alternative specifications of systemic risk measures. For each of the two main indicators used in the study – ΔCoVaR and SRISK – we substituted conceptually equivalent, yet methodologically distinct, alternatives: DSRI in the place of ΔCoVaR and Quasi-Leverage at Risk (QLaR) in the place of SRISK. These alternatives maintain a parallel structure to the original metrics, making them suitable for consistency checks.

DSRI model is a time-varying correlation framework that captures how correlations between asset returns evolve over time. It is a valuable systemic risk measure because rising correlations among financial institutions' stock returns often signal increasing interconnectedness and a higher potential for contagion during market stress. In periods of financial turbulence, asset returns tend to move more closely together, reducing diversification benefits and amplifying systemic risk (cf. Engle, 2009; Mundra & Bicchal, 2021). DSRI enables the detection of such shifts by modeling both individual volatilities and the dynamic structure of correlations, providing a nuanced view of how risks can propagate across institutions. Therefore, sustained increases in this risk index can act as an early warning indicator of systemic vulnerability and fragility in the financial system. We define DSRI as follows:

$$DSRI_{i,t} = \sqrt{\varphi_{i,0} + \varphi_{i,1} DSRI^2_{i,t-1} + \varphi_{i,2} \varepsilon^2_{i,t-1}}, \tag{22}$$

where $DSRI_{i,t}$ is the time-varying value of the conditional standard deviation of each banking institution $i$ at time $t$, $DSRI_{i,t-1}$ is the time-varying value of the conditional standard deviation of each banking institution $i$ at time $t-1$, $\varphi_{i,0}$ is the intercept, $\varphi_{i,1}$ and $\varphi_{i,2}$ are additional model parameters.

In turn, the QLaR is an effective tool for assessing systemic risk in financial institutions, because it captures the interaction between firm-level volatility and market-wide distress. It estimates the firm's total liabilities by adjusting their book value to reflect current market valuations of equity, providing a more dynamic view of leverage (cf. Adrian, Borowiecki, & Tepper, 2021). It is particularly useful when market data is more timely or reliable than book values, especially during periods of financial instability. By incorporating the market value of equity, quasi-leverage offers a forward-looking assessment of a firm's financial structure, aiding in the evaluation of its potential contribution to systemic risk. We define QLaR as:

$$QLaR_{i,t} = \frac{LI_t\left(LBL_{i,D(t)}\right)}{MC_{i,t}} - 1, \tag{23}$$

where $LBL_{D(t)}$ is the level of liabilities of bank $i$ at period $D(t)$ encompassing day $t$, $LI_t$ is piecewise linear interpolation transformation synchronizing data frequencies, and $MC_{i,t}$ is the market capitalization of bank $i$ at time $t$.

To ensure methodological transparency and comparability, we estimated both robustness measures in *R* on the same data set and in accordance with the estimation procedures described previously and applied to baseline systemic risk measures.

Table 6 presents the Kendall’s tau correlation coefficients calculated for each pair of rankings included in the study. In both cases, we observed strong alignment between rankings, with tau coefficients close to 1 and statistically significant with very low p-values, indicating that our E-factor maintains its interpretative value across different systemic risk frameworks.

Lastly, we examined robustness with respect to the environmental score provider. In this step, we used the Bloomberg Environmental pillar score (hereafter: “Eb-score”) as an alternative to the Refinitiv E-score. Unlike Refinitiv, which relies on a weighted aggregation of discrete environmental indicators, Bloomberg’s environmental pillar aggregates over 100 data points across emissions, energy, water, supply chain practices and environmental policy disclosures, with a strong emphasis on raw, reported data. This methodological divergence ensured that our robustness check was sufficiently stringent.

We re-estimated our E-factor using the Bloomberg Eb-score in place of the Refinitiv E-score, producing a parallel set of E-factor time series (termed Eb-factor) (see Appendix). Although the nominal levels of the Bloomberg-based scores differ substantially from Refinitiv’s, our factor construction method yields Eb-factors that closely track the dynamics of their Reuters-based counterparts. Figures A41 to A80 present the trajectories for both E-factors across 19 banks. The similarity in paths – despite differences in absolute values – demonstrates that our factor approach effectively mitigates inconsistencies inherent in the source data.

Owing to data availability constraints, we are unable to generate Bloomberg-based rankings; longitudinal data are available for only 10 banks, which is insufficient for a reliable comparative ranking. A comprehensive construction of Bloomberg-based rankings remains a subject for future research, contingent upon the availability of sufficiently extensive and consistent longitudinal data to support robust comparative analysis. Nevertheless, the visual consistency between E-factor and Eb-factor trends suggests that our rankings would likely remain robust under this alternative specification.

## Implications for research, practice and society

This study contributes to the growing body of research that bridges theoretical and practical climate risk impact measurement and management. Integrating climate-related financial

**Table 6.** Kendall’s tau correlation coefficients for pairs of rankings for the whole study period and subperiods

| | 2007–2009 | 2010–2013 | 2014–2019 | 2020–2021 | 2022–2023 | 2007–2023 |
|---|---|---|---|---|---|---|
| number of banks | 17 | 18 | 20 | 20 | 18 | 20 |
| E-ΔCoVaR vs. E-SRISK | 0.989$^{***}$ | 0.989$^{***}$ | 0.968$^{***}$ | 0.926$^{***}$ | 1.000$^{***}$ | 0.979$^{***}$ |
| E-ΔCoVaR vs. E-DSRI | 1.000$^{***}$ | 0.989$^{***}$ | 0.989$^{***}$ | 1.000$^{***}$ | 1.000$^{***}$ | 0.989$^{***}$ |
| E-SRISK vs. E-QLAR | 0.989$^{***}$ | 1.000$^{***}$ | 0.989$^{***}$ | 0.989$^{***}$ | 1.000$^{***}$ | 0.916$^{***}$ |
| E-ΔCoVaR vs. E-QLAR | 0.989$^{***}$ | 0.989$^{***}$ | 0.968$^{***}$ | 0.926$^{***}$ | 1.000$^{***}$ | 0.979$^{***}$ |
| E-SRISK vs. E-DSRI | 1.000$^{***}$ | 0.989$^{***}$ | 0.989$^{***}$ | 1.000$^{***}$ | 1.000$^{***}$ | 0.989$^{***}$ |
| E-DCC vs. E- QLAR | 0.989$^{***}$ | 1.000$^{***}$ | 0.989$^{***}$ | 0.989$^{***}$ | 1.000$^{***}$ | 0.916$^{***}$ |
| Average coefficient | 0.988 | 0.995 | 0.982 | 0.946 | 1.000 | 0.946 |

**Note(s):** $^{***}$ indicates statistical significance at the 0.05 significance level

**Source(s):** Own elaboration

risks into systemic risk rankings provides a foundation for further scholarly and policy-related exploration and refinement. Moreover, the proposed framework offers a structured approach that policymakers and academics can use to develop more effective risk mitigation strategies.

From a policy and regulatory perspective, the findings have significant implications for financial stability monitoring and systemic risk management. Regulators and financial institutions can leverage the proposed ranking methods to identify environmentally vulnerable banks, encouraging them to implement more targeted interventions to mitigate climate-related financial risks. Enhanced monitoring of weak links and exposures within the banking sector can help regulators anticipate systemic disruptions and require banks to strengthen buffers against climate-induced shocks. Over the long term, this research could influence regulatory frameworks by encouraging the integration of climate risk considerations into financial stability assessments, ultimately reducing spillover effects and systemic crises. The study also highlights the importance of using high-quality, proprietary data to ensure a more robust application of the proposed methodologies.

For bank management, understanding systemic exposure to environmental risk can drive improvements in internal risk management practices. By applying the proposed methodology, banks can better assess their vulnerabilities and take proactive steps to manage risk more effectively. Increased awareness of climate-related exposures may lead to shifts in corporate strategy, encouraging banks to align their operations with sustainable finance principles and integrate climate considerations into long-term planning.

Investment decisions can also benefit from the insights provided in this study. Investors in the broader stock market can use systemic risk rankings that incorporate environmental risk data to refine their strategies. This can enhance the effectiveness of ESG considerations in investment decisions, allowing for more informed choices that account for both financial and environmental risks. A more sophisticated approach to climate-aware investing could drive capital toward sustainable initiatives while discouraging support for carbon-intensive industries, positively affecting real change.

On a societal level, this research underscores the broader economic and environmental implications of climate risk in banking. By improving financial system resilience, the study contributes to economic system stability, reducing the frequency and severity of financial crises triggered by environmental shocks. Furthermore, greater transparency regarding banks' environmental risk exposure can inform public policy, reinforcing the shift toward green finance and sustainable banking. As financial institutions become more attuned to climate-related risks, they may increasingly support eco-friendly solutions, accelerating the transition to a more sustainable economy. Over time, this shift could result in a financial sector that is not only more resilient but also more aligned with the long-term interests of society and the environment.

### *Study limitations*

Acquiring relevant ESG data, especially in the face of the temporal gaps in databases, presented an additional challenge, particularly for emerging and frontier markets. To minimize the impact of these limitations on the obtained results, we selected the ESG score provider that had the highest completeness among the considered frameworks and we optimized bank selection for the illustrative application exercise to ensure that despite the CEE region data constraints it would capture the contrasts between Western, CEE banks, at the same time creating a more balanced and representative data set.

One inherent limitation in applying ESG-based methodologies lies in the substantial discrepancies observed between ESG scores across different providers. These divergences – rooted in varying definitions, measurement approaches, weighting schemes and data quality – make it difficult to determine which score most accurately captures underlying environmental risks. This ambiguity constrains the direct application of ESG scores in systemic risk modeling. To address this limitation, we focused exclusively on the environmental pillar, which has been shown to be the most objective and least affected by inter-agency inconsistencies. Moreover, rather than relying on the raw E-score, we reconstructed a dynamic and standardized E-factor through a methodological transformation that isolated and objectified the environmental signal embedded in the score. By doing so, we limited provider-specific biases to more accurately reflect the influence of environmental risks on systemic vulnerability. This framework offered a significantly more robust foundation for assessing the environmental dimension of financial system stability.

Estimating systemic risk measures like ΔCoVaR comes with certain challenges. The models used must be adaptable to data from various European stock exchanges, which requires synchronization to account for differences in trading days. This discrepancy introduces some uncertainty compared to a scenario with fully aligned exchanges. To mitigate these issues, we employed flexible EGARCH and GARCH-ADCC models with low-lag autoregressions, allowing for asymmetry while avoiding over-parameterization and ensuring model consistency. For variations in listing days, we dynamically adjusted systemic importance weights, proportionally recalculating them based on the number of banks traded on a given day. Furthermore, systemic risk estimation is significantly exposed to model risk; thus, we applied the same estimation methods with the same adjustments to all systemic risk measures used in the study to maintain comparability.

Another critical limitation pertains to the estimation of beta coefficients. Accurate beta estimation requires high-frequency, stable time series data – an assumption that research often violates, particularly in the context of emerging markets such as the CEE region, where data gaps and structural discontinuities are prevalent. In response to this challenge, we designed a ranking methodology that is explicitly beta-independent. By constructing rankings based on the relative surplus of E-augmented risk measures over their respective baselines, we circumvented the need to rely directly on beta estimates. This approach enhanced the robustness of our results and ensured that systemic risk assessments remained valid even in data-constrained environments.

## Conclusions

This study introduced a novel approach that extends traditional systemic risk measurement by incorporating environmental risk exposure – referred to as the E-factor – into the analysis. This represents an important advancement, as current systemic risk methodologies typically do not allow for the explicit quantification of environmental risk. Building on recent developments in systemic risk analysis and empirical research on the influence of ESG factors in the banking sector, we proposed a method to extract the E-factor from environmental scores (E-scores) and integrated it into systemic risk assessment.

To incorporate the E-factor into systemic risk analysis, we adopted an exposure-based approach, utilizing existing environmental scores as proxies for banks' exposure to environmental risks. Specifically, we applied two econometric systemic risk models – SRISK and ΔCoVaR – and augmented them with the E-factor, which we extracted from the Refinitiv Environmental Score using a conditional sensitivity function.

Using publicly available data, we demonstrated the empirical application of our enhanced risk measures – E-SRISK and E-ΔCoVaR – on a sample of 20 systemically important European banks from 12 countries, covering a diverse range of economic development levels. The sample included banks from highly developed economies such as Germany and Sweden, as well as from less developed countries such as Romania and Russia. The data spanned the period from 2007 to 2023.

Our results, presented as the time series of baseline and E-augmented systemic risk measures, revealed that the E-factor's impact was most pronounced during periods of financial instability. These periods coincide with major systemic events, including the global financial crisis, the European sovereign debt crisis, the COVID-19 pandemic and the war in Ukraine. The E-factor had a stronger effect on SRISK in banks with higher financial fragility and on $\Delta$CoVaR in banks more vulnerable to external shocks. This pattern held across both developed and emerging markets and for both global and local systemically important financial institutions. Notably, we observed significant geographic variation, with higher quantified environmental risk in CEE, particularly among banks in Russia, Romania and Poland – highlighting the heightened environmental risk in these regions. We also detected potential indicators of greenwashing in the CEE region.

Our findings were robust across alternative systemic risk models and, to the extent comparable, and consistent across two different ESG data providers. Furthermore, we demonstrated that the proposed beta-independent ranking methods offered additional value by enabling a different prioritization of systemically important banks based on their systemic environmental risk exposure rather than on raw E-scores. This differentiation can be particularly useful for regulators, helping to identify banks that may be more vulnerable to losses in the event of an environmental crisis.

Importantly, the proposed methodology is technically universal and can be applied to other systemic risk models beyond the four discussed in this article. While we primarily used ESG scores from Refinitiv and Bloomberg, our approach is compatible with environmental scores from any data provider, allowing for broad applicability.

This study did not aim to provide a comprehensive application of the method but rather to illustrate its analytical utility through carefully selected cases. Therefore, several avenues for further research emerged. Once a more comprehensive data set emerges with increasing data availability, future studies could explore alternative systemic risk measures and scoring methodologies, incorporating proprietary regulatory data or newly available climate risk reporting under evolving EU regulations. Comparative analyses could identify systematic relationships and regional contrasts, enhancing the understanding of risk dynamics across different financial environments. Finally, expanding the sample size to include all banks or specific subgroups could allow for a more detailed heterogeneity analysis, shedding light on variations in systemic risk across different categories of financial institutions.

Beyond banking, researchers or regulators could apply the proposed approach to other financial sectors, such as insurance, where measures like SRISK or CoVaR are relevant for assessing systemic risk. Investigating these risk measures across diverse financial entities could provide insights into the broader applicability of systemic risk modeling. Application beyond the financial sector is also possible, where it could be worthwhile to quantify the environmental risk exposure of listed companies by applying the methods proposed here. Furthermore, integrating alternative data sources could refine risk assessments, offering regulators and policymakers a more comprehensive perspective. These extensions would strengthen the methodological framework while broadening its practical implications for financial stability analysis.

## Notes

1. On a similar note, Zhang, Zhang, & Lu (2022) show how environmental changes, especially low-carbon transition, influence the banking sector’s risk and prove that climate policy impacts banking stability, which causes policy implications for macro-prudential regulations.
2. Eratalay and Cortés Ángel (2022) draw similar conclusions based on a larger-scale study of blue-chip firms, of which 63 are financial institutions (27 are banks), while Jung *et al*. (2021) demonstrate how the mechanics of the SRISK model can serve to formulate a climate risk measure for the financial system.
3. Readers may find the details regarding the construction of the applied GARCH models at V-Lab: https://vlab.stern.nyu.edu/doc?topic=mdls.

4. Berg *et al*. (2022) show that fundamental information included in ESG scores is systematically convergent. Both studies suggest that the E-factor extracted from different scores would have a similar impact on the augmented systemic risk measures. Nevertheless, the validation of this hypothesis remains beyond the scope of this article.

### Supplementary material

The supplementary material for this article can be found online.

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