E-SRISK – a method to quantify the environmental factor in systemic risk analysis

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[This version: 26.08.2022]

Abstract

We develop a new method that quantifies environmental risk in systemic risk measurement. We take the exposure approach using an existing E-score as the source of information about bank exposure to environmental risks. 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 the econometric systemic risk model (SRISK) developed by Brownlees and Engle (2017) to quantify systemic risk, and we add the E-factor using a conditional sensitivity function. Our method allows basing the impact of environmental risk exposure on individual characteristics of banks and their systemic risk levels. We demonstrate our method empirically on a sample of 19 systemically important European banks from 12 countries between 2006 and 2021. The application exercise shows that the impact of the environmental risk factor is bigger in three periods of instability: the global financial crisis, the European public debt crisis, and the COVID-19 pandemic. Moreover, the E-factor has a higher impact on SRISK of more fragile banks. This observation holds for banks from developed and emerging countries, for both global and local SIFIs. Based on the E-SRISK rankings, we observe a geographic variability between Western Europe and the CEE region. Higher environmental risk is quantified for the latter, with Russian banks at the bottom of the environmental risk ranking – signifying the severity of environmental risk generated in this country. Our solution is universal in the technical sense and applicable to other systemic risk measures and other environmental scores.

Keywords: systemic risk, financial stability, environmental risk, econometric methods

JEL Classification: G21, Q51, C32

Introduction

Systemic risk has been increasing over the last 20 years. Between 2006 and now, we have witnessed unprecedented growth of the banking systems across the world, the biggest financial crisis in history, and an unprecedented public debt crisis on an international scale. Then, years of recession and negative interest rates followed, coupled with the global pandemic that froze economies and markets in a way unobserved before. It makes systemic risk a fascinating and challenging topic for analysis, simultaneously making it a very important phenomenon to model using elaborate econometric tools.

There are many definitions of systemic risk – the most complex type of risk in finance and economics. CFA Systemic Risk Council provides a concise definition that captures the main features of this risk well. According to it, "systemic risk refers to the risk of a breakdown of an entire system rather than simply the failure of individual parts, and it "denotes the risk of a cascading failure in the financial sector, caused by linkages within the financial system, resulting in a severe economic downturn"(CFA 2022).

There are three general aspects to systemic risk: systemic liquidity (market-specific), fragility (institution-specific), and risk spill-over effect (market-specific). Research shows (Benoit et al. 2017, Silva et al. 2017) that different risk factors drive these characteristics. Therefore there is a strong argument for measuring (modeling) them using different econometric tools[1]. Looking at systemic risk in this way is also beneficial for another reason. Disentangling systemic risk into the three mentioned categories allows for capturing various important risk factors in measurement with better precision.

In the remainder of the paper, we focus on one aspect of systemic risk – fragility. It measures the financial distress of the bank operating in a distressed financial system. The best-known measure of fragility is SRISK, proposed by Brownlees and Engle (2017). One may say that this measure is among, if not the, best golden standard of systemic risk measurement if one wants to quantify the systemic risk of individual banks.

Systemic risk affects economic systems worsening the living standard and distressing society in various ways. Among them, we also find ecology-related issues. Research shows that crises slow down the transition towards 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, the ecological factors play a more crucial role on the other side of the systemic risk equation, i.e., as the drivers of systemic risk, and having reliable information on the exposure of banks to ecologically driven risk factors would be very beneficial to the regulators and the financial industry as such (compare Toma and Stefanelli 2022).

Environmental factors have been recognized as an essential part of systemic risk for several years, most recently by the most influential organizations that deal with this type of risk. Climate change has been recognized as an emerging threat to financial system stability, among others, by the Bank of International Settlements (2021), European Securities and Markets Authority (2022), European Systemic Risk Board (2021), European Banking Authority (2022), and the Financial Stability Oversight

[1] However, systemic risk materializes with the highest possible impact once all three aspects of it overlap. So it requires also a joint analysis of the three factors if one wants to measure it for the financial systems, rather than financial institutions as such.

Council (2021). Likewise, central banks point to environmental risk factors in systemic risk-related reports (e.g., BoE 2018, BoE 2021, ECB 2019, 2022, FSOC 2021, IMF 2022)[2].

Much attention is on one aspect of environmental risk: 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 by the materialization of catastrophic risk), transition risks (risks to cash flows related to the transition towards green energy), and liability risks (related to potential compensation payouts). Similarly, BIS (2021) points out that risk categories present in the Basel Framework (credit, market, liquidity, and operational risk) are affected by climate change risks (compare: 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).

Brunetti et al. (2021) point out 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 research further 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), point out that the emerging policy frameworks designed for dealing with climate-related financial risks (CRFR) 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) argue that no papers offer an analytical framework for combating climate risk using financial management and internal control tools.

So far, the use of econometric methods researching the impact of environmental risk factors on systemic risk analysis is limited. Also, even simpler quantitative econometric methods that capture climate and other environmental risks in systemic risk analysis are scarce. Among the few quantitative empirical papers, we may find a paper by Battiston et al. (2021), who investigate the spill-over of risk in stylized networks and report that the risks generated by climate-related events can be systemic.

The other significant paper is that of Jung et al. (2021), who propose 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, this method considers only a fraction of the environmental risk exposure, disregarding other environmental factors beyond climate risk. For many financial institutions in Europe, such a narrowed scope is insufficient if one wants to capture all the actual environmental risk exposure in systemic risk analysis.

There are also papers researching the link between green finance and larger-scale risk and its impact on societies. For instance, Sohag et al. (2022) show that green investments are sensitive to geopolitical risk in terms of shock transmission. Wang et al. (2022) demonstrate that green finance positively affects green innovation in emerging countries. At the same time, Tol (2019) shows that national social costs of carbon emissions are the largest in developing countries with large populations, while income convergence raises these costs.

[2] On a similar note, Zang et al. (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.

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 ESG (environmental, social, and governance) factors exposure to be used by large banks starting from 2023 (EBA 2022). At the same time, European Central Bank (2021) performed ECB economy-wide climate stress test and is currently running the first climate risk stress test developed to assess the susceptibility of European banks to climate-change-related shocks (ECB 2022). The results of the 2021 stress test 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.

On the other hand, there is extensive research on the ESG factors in the investment-focused frameworks (for reviews, see, e.g., Billio et al. 2021, Gillian et al. 2021, Berg et al. 2022). ESG scores are a tool that intends to capture how companies and investors include the environmental, social, and governance aspects in their business (e.g., Scholtens 2006, Cornett et al. 2016, Bahadori 2021, Liu et al. 2021), investment (e.g., Cormier et al. 2011, Renneboog 2011, Bătae, Voicu, and Feleagă 2020, Wong and Zang 2022) and risk management decisions (e.g., Lee and Faff 2009, Bouslah et al. 2013, 2018, Sassen et al. 2016, Albuquerque et al. 2019, Boubaker et al. 2020, Kim et al. 2021).

Only several papers focus on the relationship between the 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. 2016, Finger et al. 2018, Gangi et al. 2019, Brunetti e al. 2021, Chiaramonte 2021, Mure et al. 2021, Neitzert and Petras 2021). Other papers focus on the risk of the financial systems (e.g., Anginer et al. 2014, 2018, Cerqueti et al. 2021). Regretfully, none of these findings can be a base for econometric methods measuring systemic risk.

In one of the most recent papers, Aevoae et al. (2022) investigate the relationship between ESG scores and systemic risk. In particular, 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 and Brunnermeier 2016). At the same time, they use SRISK (Brownlees and Engle 2017) for their robustness checks. Their results indicate a statistically significant relationship between the changes in ESG scores and SRISK for the 14-year period between 2007 and 2020. This relation is robust for financial systems in advanced economies, and it is particularly strong for the environmental factor (Aevoae 2022, p. 4, 16-20). It is one of the two empirical analyses (the first being the aforementioned CRISK model) using a large sample of banks, proving that the environmental risk factor significantly influences SRISK[3]. Also, the study quantifies the size of this impact in an economically meaningful manner.

Despite the ample evidence of the importance of quantifying all of the environmental risks in systemic risk analysis, very few methods quantify it going beyond climate risk. Moreover, when it comes to econometric methods of systemic risk measurement developed after the global financial crisis that gained recognition, none of such measures in their current shape includes all environmental risk explicitly.

The primary purpose of this paper is to present a new method that allows adding the environmental factor (E-factor) to systemic risk measurement. Since current systemic risk measurement methods do not quantify the E-factor, we address this 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 ground for a meaningful introduction of the E-factor to systemic risk

[3]Eratalay and Cortes Angel (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 be used to formulate a climate risk measure for the financial system.

analysis. Notably, although applied to SRISK in this paper, the solution that we propose is universal in the technical sense and applicable to other econometric systemic risk measures.

In the remaining part of the paper, we present our econometric methods, discuss how we extract the environmental risk factor from the ESG score, and how we augment the SRISK measure with it, using a beta-independent exposure-based approach. Then we demonstrate the application of our method to empirical data using a sample of systemically important European banks. Afterward, we provide 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.

Materials and Methods

To augment systemic risk analysis with the environmental risk factor, we take the exposure approach recommended by the European Banking Authority (EBA 2022) as one of the possible frameworks. Such an approach assumes using a readily available environmental score as the source of information about bank exposure to environmental risks.

Taking this approach has several benefits going beyond the usage of readily available public data. As The Financial Stability Board argues in one of its recommendations on monitoring of environmental risks, third-party verification is potentially beneficial to strengthen the reliability of environmental risk data, while relying on external metrics available to authorities and broader financial market participants "could play an important role in avoiding greenwashing risks" (FSB 2022, *Recommendation II*).

Also, as EBA (2021) points out, the ESG ratings provided by specialized rating agencies are direct in taking into account the risk exposure to ESG factors as well as the management's ability to deal with risks or opportunities. This human factor is difficult to quantify systematically in risk measurement directly. 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.

We apply a sophisticated econometric systemic risk model SRISK developed by Brownlees and Engle (2017) to quantify systemic risk, and we add the E-factor extracted from the Environmental score (E-score) using a conditional sensitivity function presented below.

SRISK

SRISK is a systemic risk measure that quantifies the fragility of each financial institution, such as a commercial bank. This measure assumes the conditionality of individual bank risk on the state of distress of the financial system.

To calculate the daily values of the SRISK for each analyzed bank, we define the financial system s as a composite of banks i, where $i = 1, \dots, N$ of financial institutions, including the most systemically significant ones (SIFIs). To identify SIFI, we use the guidance of the European Banking Authority (2020). As a proxy of the financial system, we use the *Country-Datastream Banks*[4] index taken

[4] In case of two countries: Hungary and Russia, we take a slightly broader financial sector index that includes not only banks, but also the insurance and investment funds data, as the banking sector index is either unavailable for the studied period (Russia) or the index does not meet the conditions required for SRISK calculation (too few banks – Hungary).

individually for each analyzed country (a country where a given bank is headquartered). The rate of return for the financial system s at time t we denote as $r_{s,t}$ and for institutions i as $r_{i,t}$. 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 $\mathbb{P}\left(r_{i,t} \leq VaR_{i,t}^{q}\right) = q$, $VaR_{i,t}^{q}$ 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.

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

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

Based on ES, we derive the Marginal Expected Shortfall (MES) as a partial derivative defined as:

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

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

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

where γ is the correcting factor relative to the length of the assumed horizon. In the current study, we assume that long-run market decline corresponds to a 40% loss over the horizon of six months (cf. Engle and Zazzara 2018). Assuming the negative definition of risk, we ignore any negative values of SRISK (i.e., any potential capital surpluses). Thus, the SRISK equals:

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

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. In this paper, we assume the k parameter at 8%, which follows Brownlees and Engle (2017), as well as Engle and Zazzara (2018).

Estimation

We estimate model parameters following the literature (Brownlees and Engle 2017, Benoit et al. 2014, 2017). To model conditional volatility, we use the GJR-GARCH approach, and to model dynamic correlation, we use the GARCH-DCC (compare: *V-Lab Documentation*[5]), where r_t is the vector of $\left(r_{s,t}, r_{i,t}\right)$ at time t, and r_t is the conditional variance-covariance matrix at time t:

$$r_t = \sqrt{C_t}v_t, \tag{7}$$

The matrix takes the form of:

[5] The details regarding the construction of the applied GARCH models may be found at V-Lab: https://vlab.stern.nyu.edu/doc?topic=mdls.

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

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

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

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

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

and

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

Then long-run MES is estimated as:

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

and SRISK as:

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

For empirical calculations, we use the SRISK measure expressed as a percentage of market capitalization, i.e., SRISK(%).

Augmenting for the environmental factor

The augmentation of the SRISK measure with the E-factor consists of its rescaling, following the logic that the lower the environmental pillar score is, the more the SRISK value increases.

To model this relationship, we synchronize the frequency of the SRISK and the E-score series quotations by assigning the annual environmental quotation to the middle business/trading day (earlier of both, if two) of the following year. Afterward, we extend the obtained quotations to all business/trading days using piecewise linear interpolation. Additionally, the last available annual quotation is maintained 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. We base this procedure on the assumption 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 impacts systemic risk in the following period until new information becomes available. Such an approach is motivated by the findings of behavioral finance theory (Kahneman 2013).

Then we use the equation, where we define the E-SRISK(%) as:

$$E\_SRISK_{i,t} = SRISK_{i,t}\left(1 + \beta\left(100 - E_{i,t}\right)\right), \tag{14}$$

In the equation above, $SRISK_{i,t}$ and $E_{i,t}$ stand for the SRISK(%) and the E-score, respectively, and each relates to a bank i at a business/trading day t.

Algebraic operations allow rewriting equation (14) as:

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

Equation (15) demonstrates that the increase in E-SRISK(%) is proportional to the decrease in the E-score, while the scale of this change depends on the current SRISK level – the higher the current level of SRISK, the stronger the impact. Moreover, if SRISK decays to zero, the influence of the E-score on SRISK 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 recommendations of the EBA (2022).

We also note that the β coefficient may take a form of a function of time, i.d. $\beta = \beta(t)$. 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 T be the set of days from a fixed time horizon. Then the surplus area for a given institution/bank is calculated as:

$$SURP_i(T) = \frac{\sum_{t\in T} E\_SRISK_{i,t}}{\sum_{t\in T} SRISK_{i,t}} - 1 = \frac{\sum_{t\in T} \beta\left(100-E_{i,t}\right)SRISK_{i,t}}{\sum_{t\in T} SRISK_{i,t}}. \tag{16}$$

Since formula (15) holds, it yields that:

$$SURP_i(T) = \beta \cdot \frac{\sum_{t\in T}\left(100-E_{i,t}\right)SRISK_{i,t}}{\sum_{t\in T} SRISK_{i,t}}, \tag{17}$$

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 E-SRISK, $SURP_i(T)$, will not depend on the choice of the coefficient value. We use this feature of our model in the following empirical section.

In this paper, we use and augment the SRISK measure. However, the proposed method is applicable to any other systemic risk measure for which a significant relationship between the E-score and systemic risk levels can be proven. Such an alternative measure might be, for instance, Delta CoVaR (Adrian and Brunnermeier 2016). Furthermore, even though we use the ESG scores provided by the Thomson Reuters Refinitiv database, the presented method allows extracting the E-factor from any existing environmental score[6].

[6] Berg et al 2021 show that for investment and risk management purposes different existing scores provide very similar information, while Berg, Kolbel and Rigobon (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 E-SRISK. Nevertheless, the validation of this hypothesis remains beyond the scope of this paper.

Data

Based on publicly available data, we quantify E-SRISK – systemic risk augmented with the E-factor for a diversified sample of 19 banks from 12 different European countries (both advanced and emerging economies), including Austria, Belgium, France, Germany, Greece, Hungary, Italy, The Netherlands, Poland, Romania, Russia, Sweden. The empirical data sample encompasses the period from 2006 to 2021, including approximately 76,600 observations regarding the analyzed banks' stock prices, over 3000 entries of the *Country-Data Stream Banks* index, and all available entries on the ESG scores in the sampled period, from which we extract the E-factor on the Environmental score (hereafter E-score). The Appendix contains the descriptive statistics, as well as the list of the analyzed banks and indices. The source of all data used in this paper is Reuters Refinitiv Eikon and Datastream.

The E-score is part of the ESG Score calculated according to the Thomson Reuters Refinitiv methodology (2021) 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, 22 data points are used per bank yearly, while the multipliers of the mentioned three pillars are 1 (weight 0.17), 4 (0.67), and 1 (0.17), 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.

Model application to empirical data

The following section illustrates how the model works on actual empirical data. For the case study presented here, we assume the value of $\beta = 0{,}95\%$, which is in line with the findings of the two most recent empirical papers, both of which come to a very similar conclusion regarding the size of the systemic impact of the environmental factor (compare: Aevoae et al. 2022, Eratalay and Cortés Ángel 2022). They are also in line with the most recent stress test of the European Central bank (2021) as to the magnitude of the modeled effect. Let it be stressed, however, that 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 the Appendix. Mentioned graphs present the results obtained for each analyzed bank, where the black time series represents the time-varying values of the baseline SRISK(%) measure, and the green line indicates the values of SRISK(%) augmented with the E-factor.

Generally speaking, we see that the impact of the E-factor is 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, or the recent COVID-19 pandemic. We also see that the E-factor has a higher impact on SRISK(%), the higher general level of fragility of a given bank. This observation is valid for banks from developed and emerging countries. It is also relevant for all banks, regardless of whether they are global SIFIs or not (compare Table A1 in the Appendix). There is, however, an evident geographic variability observable.

We can distinguish banks characterized by a high E-score throughout the study period in the sample. They include French, German, Italian and Dutch banks which brand themselves around ecological solutions and sustainability, such as Société Générale S.A. (France), Commerzbank AG and Deutsche Bank AG (Germany), UniCredit S.p.A. and Intesa San Paolo S.p.A. (Italy), and ING Bank NV (The Netherlands). On the opposite side of the spectrum, we find several systemic banks from Central Europe, including a Romanian bank (Banca Transilvania SA), a Hungarian one (OTP Bank Nyrt), two Polish banks (PKO BP SA and mBank SA), and one Western European bank that has a substantial presence in the CEE region – Raiffeisen Bank International AG. The highest impact of the E-factor – corresponding to very low E-scores, pointing to severe environmental systemic risk – is found in Russia (Sberbank and VTB PAO). Figures 1 to19 in the Appendix present the discussed time series.

To quantify the impact of the E- factor on SRISK(%) in a more meaningful way, we construct a set of beta-independent rankings of the analyzed banks. We base the ranking on the ratio of the area closed by the *E-SRISK* and *SRISK* time series to the area closed by the *SRISK* and the time axis, assuming continuous time. Such a ratio (given as a percentage) expresses the surplus of the E-SRISK(%) relative to the baseline SRISK(%). In other words, it is the average risk increase caused by taking the environmental factor into account.

We use the sums of the time series values to estimate the necessary areas. The time range considered for each bank is individual and determined by the availability of both time series (*SRISK* and *E-SRISK*). Applying such a relative measure – a surplus within a fixed unit of time – allows us to correct the bias caused by the difference in individual time ranges (caused by data unavailability). Table 1 shows the ranking.

Table 1. The ranking of banks based on the surplus of the E-SRISK(%)over SRISK(%) – the whole analyzed period

Bank	Country	*SRISK*	*E-SRISK*	Total surplus
Société Générale S.A.	France	13526.67	14358.53	6.15%
Intesa San Paolo S.p.A.	Italy	4514.51	4846.66	7.36%
Deutsche Bank A.G.	Germany	17400.19	18720.07	7.59%
Commerzbank A.G.	Germany	18692.54	20613.28	10.28%
KBC Group NV	Belgium	4289.64	4757.79	10.91%
UniCredit S.p.A.	Italy	8194.32	9142.21	11.57%
ING Bank NV.	The Netherlands	7402.89	8275.09	11.78%
Skandinaviska Enskilda Banken A.B.	Sweden	3722.66	4326.23	16.21%
Swedbank A.B	Sweden	3630.43	4443.09	22.38%
ING Bank Śląski S.A	Poland	90.11	110.62	22.76%
Erste Group Bank AG.	Austria	4503.37	5588.65	24.10%
Eurobank Ergasias Srvcs and Hold SA	Greece	15874.16	20102.55	26.64%
OTP Bank Nyrt	Hungary	306.03	400.82	30.98%
mBank SA.	Poland	630.21	839.40	33.19%
Raiffeisen Bank International A.G.	Austria	4695.15	6264.29	33.42%
VTB PAO	Russia	3038.82	4317.78	42.09%
Banca Transilvania S.A.	Romania	129.38	195.64	51.22%
Sberbank	Russia	658.16	1004.63	52.64%
PKO BP S.A	Poland	217.98	335.66	53.98%

The ranking illustrates the characteristics described earlier, 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 also construct four additional rankings for the four periods in our sample characterized by different systemic turbulence: the period of the global financial crisis (August 2007 – July 2009), the period of the public debt crisis in Europe (August 2009 – December 2013), the period of prolonged low interest rates and economic stagnation (January 2014 –December 2019), and the ongoing COVID-19 pandemic (starting from January 2020). Table 2 presents these results.

Table 2. The ranking of banks based on the surplus of the E-SRISK(%) over SRISK(%) – subperiods

Bank	Country	2007 – 2009	2009 – 2013	2014 – 2019	2020 – 2021
Deutsche Bank A.G.	Germany	12.28%	10.80%	4.62%	3.95%
Société Générale S.A.	France	12.86%	5.60%	5.73%	4.73%
Intesa San Paolo S.p.A.	Italy	9.15%	6.74%	7.45%	7.58%
Skandinaviska Enskilda Banken A.B.	Sweden	20.35%	13.37%	9.95%	8.18%
KBC Group NV	Belgium	10.43%	10.92%	12.91%	8.91%
Commerzbank A.G.	Germany	10.72%	7.62%	12.64%	10.88%
UniCredit S.p.A.	Italy	13.22%	10.57%	11.78%	11.21%
ING Bank Śląski S.A	Poland	———	72.45%	62.78%	11.66%
ING Bank NV.	The Netherlands	10.49%	12.63%	10.09%	14.03%
Swedbank A.B.	Sweden	26.77%	17.26%	14.42%	17.41%
Erste Group Bank AG.	Austria	41.47%	21.25%	17.33%	18.94%
mBank SA.	Poland	———	41.33%	62.52%	25.31%
OTP Bank Nyrt	Hungary	35.08%	33.03%	27.16%	27.28%
Raiffeisen Bank I.A.G.	Austria	64.74%	37.41%	23.67%	34.30%
Eurobank Ergasias Srvcs and Hold SA	Greece	28.30%	27.58%	21.87%	34.87%
Banca Transilvania S.A.	Romania	———	———	91.84%	35.36%
VTB PAO	Russia	0.00%	40.69%	42.01%	46.04%
PKO BP S.A	Poland	77.61%	78.61%	74.55%	47.31%
Sberbank	Russia	77.61%	53.73%	51.96%	47.45%

Differences between the periods are noticeable, with a general trend towards E-factor exposure reduction over time. Still, individual banks show different characteristics. There are banks such as, e.g., ING (Netherlands and Poland) that significantly reduced their environmental risk exposure gradually in the whole period regardless of external turbulence, and such banks that moved in the opposite direction in the past turbulent periods (e.g., PKO BP, Poland or mBank, Poland) and the current pandemic (e.g., Raiffeisen, Austria). One Russian bank (VTB) shows a constant increase in environmental risk exposure over time.

The E-SRISK-based rankings of financial institutions for all five analyzed data periods differ significantly from analogous rankings obtained from the E-score alone. These differences are more prominent during turbulent periods (the global financial crisis and the COVID-19 pandemic). For reference, please see Table A4 in Appendix. This observation confirms that integrating the E-score into a systemic risk measure, such as SRISK, captures an essential characteristic: risk factor exposures can produce higher losses in crises than in calm periods, even if the risk factors are not directly related to the crisis at hand.

Conclusions

This paper aimed to present a new method that allows adding the environmental factor (the E-factor) to systemic risk measurement since existing systemic risk measurement methods do not allow for the explicit quantification of this risk factor. Building on the most recent developments in systemic risk analysis and empirical research on the impact of the ESG factors on risk in the banking sector, we propose a method extracting the E-factor from the environmental score (E-score) and augmenting systemic risk measurement with it.

To augment systemic risk analysis with the E-factor, we take the exposure approach recommended by the European Banking Authority (EBA 2022), which assumes using an existing environmental score as the source of information about bank exposure to environmental risks. We apply an econometric systemic risk model SRISK developed by Brownlees and Engle (2017) to quantify systemic risk, and we add the E-factor extracted from the Refinitiv Environmental score (E-score) using a conditional sensitivity function.

Based on publicly available data, we demonstrate the empirical application of the augmented systemic fragility measure E-SRISK on a sample of 19 systemically important European banks from 12 countries, different on the spectrum of economic development, ranging from most developed countries such as Germany or Sweden to least developed ones, such as Romania or Russia. The empirical data sample encompasses the period from 2006 to 2021.

The results in the form of time series showing the baseline and E-SRISK, as well as the ranking prepared based on these results, show that the size of the impact of the E-factor is more extensive in the periods of instability (around the peaks) that relate to three significant systemic risk triggers including the global financial crisis, the European public debt crisis, and the COVID-19 pandemic. Moreover, the E-factor has a higher impact on SRISK, the higher the fragility of a given bank is. This observation holds for banks from developed and emerging countries for global and local SIFIs. A clear geographic variability is observable between Western Europe and the CEE region. Higher environmental risk is quantified for the latter, with Russian banks at the bottom of the environmental risk ranking – signifying the severity of this risk generated in this country.

Notably, although applied to SRISK in this paper, the solution that we propose is universal in the technical sense and applicable to any other systemic risk measure for which there can be proven a significant relationship between the E-score and systemic risk levels. Furthermore, even though we use the ESG scores provided by the Thomson Reuters Refinitiv database, the presented method also allows extracting the E-factor from any other existing environmental score.

Funding

The National Science Centre funded this research project under Agreement UMO-2018/29/N/HS4/02783.

References

Adrian, T., Brunnermeier, M.K., 2016. CoVaR. American Economic Review 106, 1705–1741.

Aevoae, G.-M., Andries, A. M., Ongena, S., Sprincean, N., ESG and Systemic Risk (March 11, 2022). Swiss Finance Institute Research Paper No. 22-25, https://ssrn.com/abstract=4058477 or http://dx.doi.org/10.2139/ssrn.4058477.

Albuquerque, R., Koskinen, Y., Zhang, C., 2019. Corporate Social Responsibility and firm risk: Theory and empirical evidence. Management Science 65, 4451–4469.

Anginer, D., Demirguc-Kunt, A., Huizinga, H., Ma, K., 2018. Corporate governance of banks and financial stability. Journal of Financial Economics 130, 327–346.

Anginer, D., Demirguc-Kunt, A., Zhu, M., 2014. How does competition affect bank systemic risk? Journal of Financial Intermediation 23, 1–26.

Bahadori, N., Kaymak, T., Seraj, M., 2021. Environmental, social, and governance factors in emerging markets: The impact on firm performance. Business Strategy & Development 4, 411–422.

Bank for International Settlements (BIS), 2021. Climate-related risk drivers and their transmission channels, Basel Committee on Banking Supervision April 2021, https://www.bis.org/bcbs/publ/d517.pdf.

Bank of England (BoE), 2018. Climate change: what are the risks to financial stability?", KnowledgeBank, November 2018, https://www.bankofengland.co.uk/knowledgebank/climate-change-what-are-the-risks-to-financial-stability.

Bank of England (BoE), 2021. Financial Stability Report. December 2021, https://www.bankofengland.co.uk/-/media/boe/files/financial-stability-report/2021/december-2021.pdf?la=en&hash=62FF3E7484FF0FD1AD650FE41A77D32B3750F8CF.

Bătae, O.M., Voicu D., Feleagă L., 2020. Environmental, Social, Governance (ESG), and Financial Performance of European Banks. Journal of Accounting and Management Information Systems 19 (3). https://doi.org/10.24818/jamis.2020.03003.

Battiston, S., 2019. The importance of being forward-looking: Managing financial stability in the face of climate risk. Banque de France Financial Stability Review No. 23 – June 2019 – Greening the Financial System: the New Frontier. Financial. Banque de France, Paris. Available at: https://www.banque-france.fr/sites/default/files/media/2019/08/27/financial_stability_review_23.pdf

Battiston, S., Dafermos, Y., Monasterolo, I., 2021. Climate risks and financial stability. Journal of Financial Stability 54, 100867.

Benoit, S., Colliard, J.-E., Hurlin, C., Pérignon, C. 2017. Where the risks lie: A survey on systemic risk. Review of Finance 21(1), 109–152.

Berg, F., Koelbel, J.F., Pavlova, A., Rigobon, R., 2021. ESG Confusion and Stock Returns: Tackling the Problem of Noise, https://papers.ssrn.com/sol3/papers.cfm?abstract_id=3941514.

Berg, F., Koelbel, J., Rigobon, R. (2022). Aggregate Confusion: The Divergence of ESG Ratings. Review of Finance, May, https://doi.org/10.1093/rof/rfac033.

Billio, M., Costola, M., Hristova, I., Latino, C., Pelizzon, L. 2021. Inside the ESG Ratings: (Dis)Agreement and Performance. Corporate Social Responsibility and Environmental Management, 28(5), 1426–1445. https://doi.org/10.1002/csr.2177

Bostandzic, D., Weiß, G.N.F., 2018. Why do some banks contribute more to global systemic risk? Journal of Financial Intermediation 35, 17–40.

Boubaker, S., Cellier, A., Manita, R., Saeed, A., 2020. Does corporate social responsibility reduce financial distress risk? Economic Modelling 91, 835–851.

Bouslah, K., Kryzanowski, L., M’Zali, B., 2013. The impact of the dimensions of social performance on firm risk. Journal of Banking & Finance 37, 1258–1273.

Bouslah, K., Kryzanowski, L., M’Zali, B., 2018. Social performance and firm risk: Impact of the financial crisis. Journal of Business Ethics 149, 643–669.

Brownlees, C., Engle, R., 2017. SRISK: A conditional capital shortfall measure of systemic risk. Review of Financial Studies 30(1), 48-79.

Brunetti, C., Dennis, B., Gates, D., Hancock, D., Ignell, D., Kiser, E., Kotta, G., Kovner, A., Rosen, R., Tabor, N. 2021. Climate Change and Financial Stability, FEDS Notes. Washington: Board of Governors of the Federal Reserve System, March, https://www.federalreserve.gov/econres/notes/feds-notes/climate-change-and-financial-stability-20210319.htm.

Cerqueti, R., Ciciretti, R., Dalò, A., Nicolosi, M., 2021. ESG investing: A chance to reduce systemic risk. Journal of Financial Stability 54, 100887.

CFA, 2022. Systemic Risk and Management in Finance. https://www.cfainstitute.org/en/advocacy/issues/systemic-risk (retrieved 23.08.2022)

Chenet, Hugues, Josh Ryan-Collins, and Frank van Lerven. 2021. "Finance, Climate-Change and Radical Uncertainty: Towards a Precautionary Approach to Financial Policy." Ecological Economics 183 (May): 106957. https://doi.org/10.1016/j.ecolecon.2021.106957.

Chiaramonte, L., Dreassi, A., Girardone, C., Piserà, S., 2021. Do ESG strategies enhance bank stability during financial turmoil? Evidence from Europe. European Journal of Finance, DOI: 10.1080/1351847X.2021.1964556.

Cormier, D., Ledoux, M., Magnan, M., 2011. The informational contribution of social and environmental disclosures for investors. Management Decision 49, 1276–1304.

Cornett, M.M., Erhemjamts, O., Tehranian, H., 2016. Greed or good deeds: An examination of the relation between corporate social responsibility and the financial performance of U.S. commercial banks around the financial crisis. Journal of Banking & Finance 70, 137–159.

Delis, M.D., de Greiff, K., Iosifidi, M., Ongena, S., 2021. Being Stranded with Fossil Fuel Reserves? Climate Policy Risk and the Pricing of Bank Loans. Swiss Finance Institute Research Paper Series No 18-10.

Eratalay, M. H., and A.P. Cortés Ángel. 2022. The Impact of ESG Ratings on the Systemic Risk of European Blue-Chip Firms Journal of Risk and Financial Management 15, no. 4: 153. https://doi.org/10.3390/jrfm15040153

European Banking Authority (EBA), 2020, O-SIIs, Other Systemically Important Institutions, https://www.eba.europa.eu/risk-analysis-and-data/other-systemically-important-institutions-o-siis-

European Banking Authority (EBA), 2021, Report on management and supervision of ESG risks for credit institutions and investment firms, https://www.eba.europa.eu/sites/default/documents/files/document_library/Publications/Reports/2021/1015656/EBA%20Report%20on%20ESG%20risks%20management%20and%20supervision.pdf

European Banking Authority (EBA), 2022. EBA publishes binding standards on Pillar 3 disclosures on ESG risks, https://www.eba.europa.eu/eba-publishes-binding-standards-pillar-3-disclosures-esg-risks.

European Central Bank (ECB), 2022. ECB Banking Supervision launches 2022 climate risk stress test, https://www.bankingsupervision.europa.eu/press/pr/date/2022/html/ssm.pr220127~bd20df4d3a.en.html?utm_source=ecb_twitter&utm_campaign=220127_pr_climate_stress_test.

European Central Bank (ECB), 2019. Financial Stability Report, May, https://www.ecb.europa.eu/pub/financial-stability/fsr/html/ecb.fsr202105~757f727fe4.en.html.

European Central Bank. 2021. Financial Stability Review, November, https://www.ecb.europa.eu/pub/pdf/fsr/ecb.fsr202111~8b0aebc817.en.pdf

European Securities and Markets Authority (ESMA), 2022. Sustainable Finance Roadmap 2022-2024, https://www.esma.europa.eu/policy-activities/sustainable-finance/sustainable-finance-roadmap-2022-2024

European Systemic Risk Board (ESRB), 2021. Climate-related risk and financial stability, https://www.esrb.europa.eu/pub/pdf/reports/esrb.climateriskfinancialstability202107~79c10eba1a.en.pdf?71a273dc36a85ef05c8bed530466f900.

The Financial Stability Board (FSB). 2022. Supervisory and Regulatory Approaches to Climate-related Risks Interim Report. April, https://www.fsb.org/2022/04/supervisory-and-regulatory-approaches-to-climate-related-risks-interim-report/

Financial Stability Oversight Council (FSOC), 2021. Report on Climate-Related Financial Risk 2021, https://home.treasury.gov/system/files/261/FSOC-Climate-Report.pdf.

Finger, M., Gavious, I., Manos, R., 2018. Environmental risk management and financial performance in the banking industry: A cross-country comparison. Journal of International Financial Markets, Institutions and Money 52, 240–261.

Forcadell, F.J., Aracil, E., 2017. European banks' reputation for corporate social responsibility. Corporate Social Responsibility and Environmental Management 24, 1–14.

Gangi, F., Meles, A., D'Angelo, E., Daniele, L.M., 2019. Sustainable development and corporate governance in the financial system: Are environmentally friendly banks less risky? Corporate Social Responsibility and Environmental Management 26, 529–547.

Gillan, S.L., Koch, A., Starks, L.T., 2021. Firms and social responsibility: A review of ESG and CSR research in corporate finance. Journal of Corporate Finance 66, 101889.

International Monetary Fund. 2022. Global Financial Stability Report. https://www.imf.org/en/Publications/GFSR/Issues/2022/04/19/global-financial-stability-report-april-2022

Jung, H., Engle, R.F., Berner, R.,2021. Climate Stress Testing. FRB of New York Staff Report No. 977, Rev. June 2022, http://dx.doi.org/10.2139/ssrn.3931516.

Kahneman, D., 2013, Thinking, fast and slow, Macmillan, New York.

Kim, S., Lee, G., Kang, H.-G., 2021. Risk management and corporate social responsibility. Strategic Management Journal 42, 202–230.

Lee, D.D., Faff, R.W., 2009. Corporate sustainability performance and idiosyncratic risk: A global perspective. Financial Review 44, 213–237.

Liu, W., Shao, X., De Sisto, M., Li, W.H., 2021. A new approach for addressing endogeneity issues in the relationship between corporate social responsibility and corporate financial performance. Finance Research Letters 39, 101623.

Murè, P., Spallone, M., Mango, F., Marzioni, S., Bittucci, L, 2021. ESG and reputation: The case of sanctioned Italian banks. Corporate Social Responsibility and Environmental Management 28(1), 265-277.

Neitzert, F., Petras, M., 2021. Corporate social responsibility and bank risk. Journal of Business Economics. https://doi.org/10.1007/s11573-021-01069-2.

Nieto, Maria. 2017. "Banks and Environmental Sustainability: Some Financial Stability Reflections." International Research Centre on Cooperative Finance October. https://doi.org/10.2139/ssrn.3082107.

Renneboog, L., Ter Horst, J., Zhang, C., 2011. Is ethical money financially smart? Nonfinancial attributes and money flows of socially responsible investment funds. Journal of Financial Intermediation 20, 562–588.

Sassen, R., Hinze, A.-K., Hardeck, I., 2016. Impact of ESG factors on firm risk in Europe. Journal of Business Economics 86, 867–904.

Scholtens, B., 2006. Finance as a driver of corporate social responsibility. Journal of Business Ethics 68, 19–33.

Sohag, K., Hammoudeh, S., Elsayed, A., Mariev, O., & Safonova, Y. (2022). Do geopolitical events transmit opportunity or threat to green markets? Decomposed measures of geopolitical risks. Energy Economics, 106068. https://doi.org/10.1016/j.eneco.2022.106068

Tol, R. S. J. (2019). A social cost of carbon for (almost) every country. Energy Economics, 83, 555–566. https://doi.org/10.1016/j.eneco.2019.07.006

Toma, P., Stefanelli, V., 2022. What Are the Banks Doing in Managing Climate Risk? Empirical Evidence from a Position Map. Ecological Economics 200 (October): 107530. https://doi.org/10.1016/j.ecolecon.2022.107530.

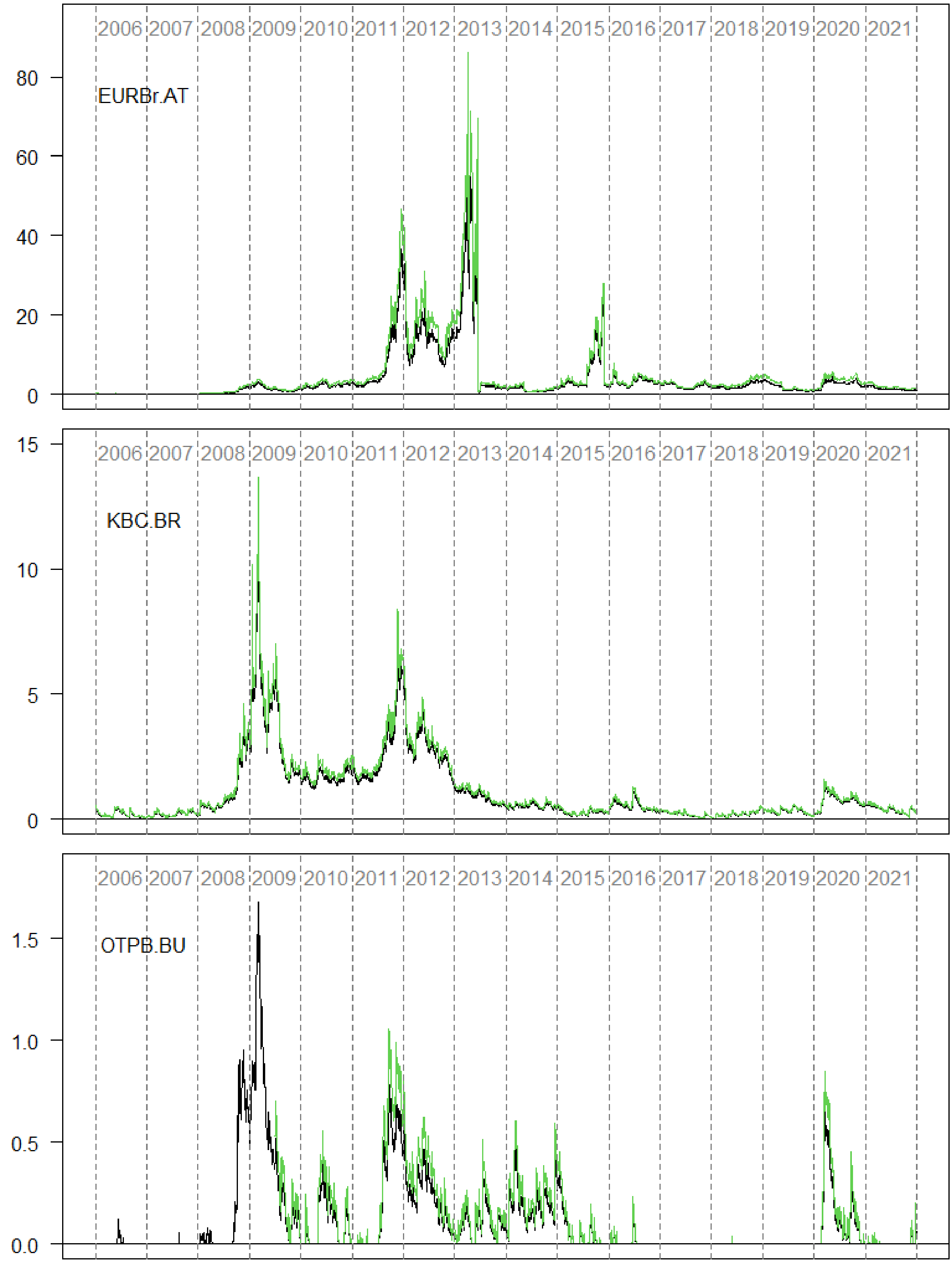
Wang, Q. J., Wang, H. J., & Chang, C. P. (2022). Environmental performance, green finance and green innovation: What's the long-run relationships among variables? Energy Economics, 110(March), 106004. https://doi.org/10.1016/j.eneco.2022.106004

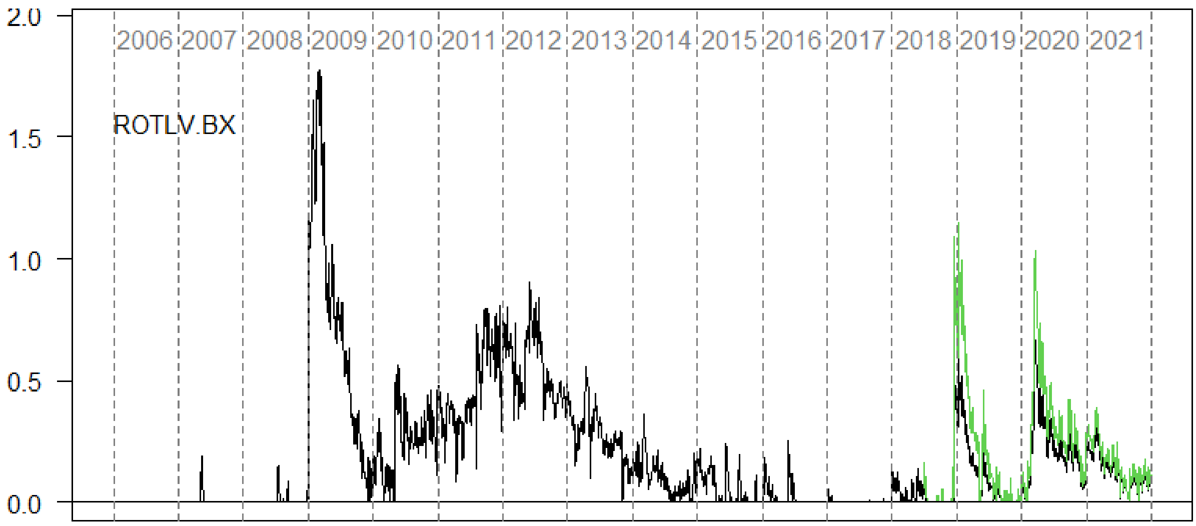
Wong, J.B., Zhang, Q., 2022. Stock market reactions to adverse ESG disclosure via media channels. The British Accounting Review 54, 101045.

Zhang, X., Zhang, S., & Lu, L. (2022). The banking instability and climate change: Evidence from China. Energy Economics, 106, 105787. https://doi.org/10.1016/j.eneco.2021.105787

Appendix

Figures A1 – A19 percentage SRISK [black] and percentage E-SRISK [green] for individual banks listed in Table A1

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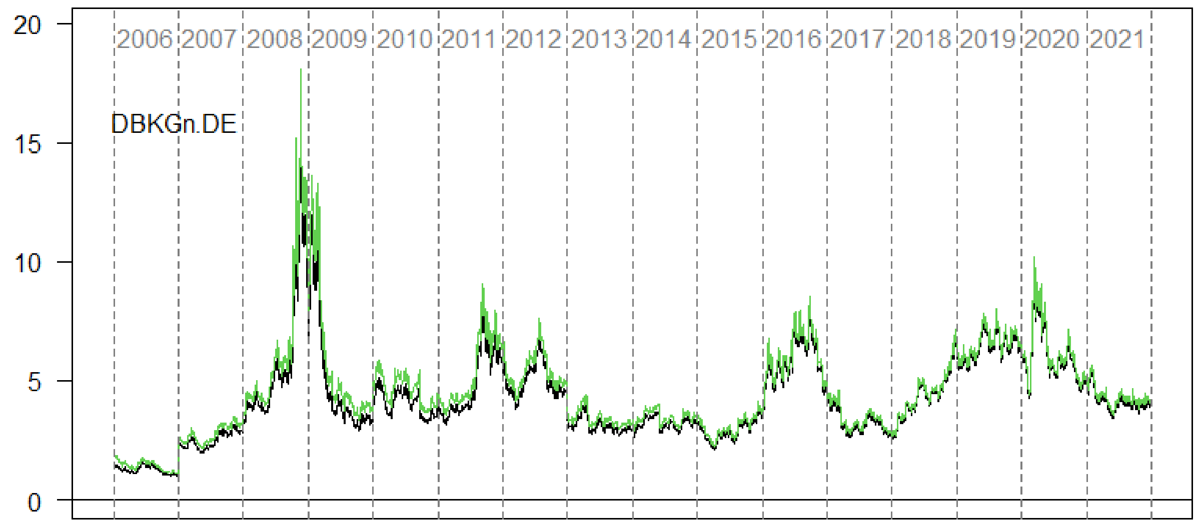
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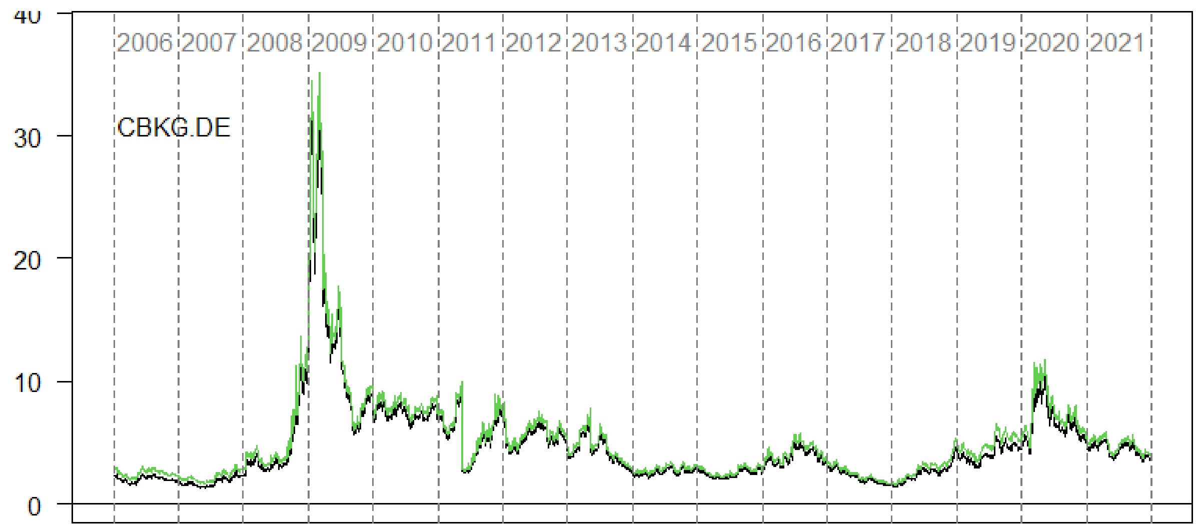
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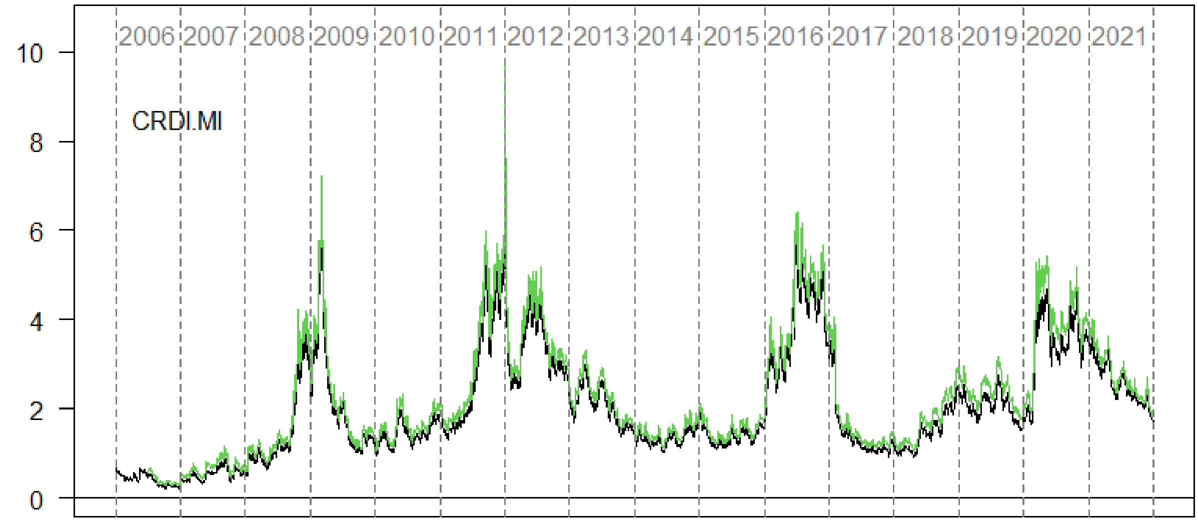
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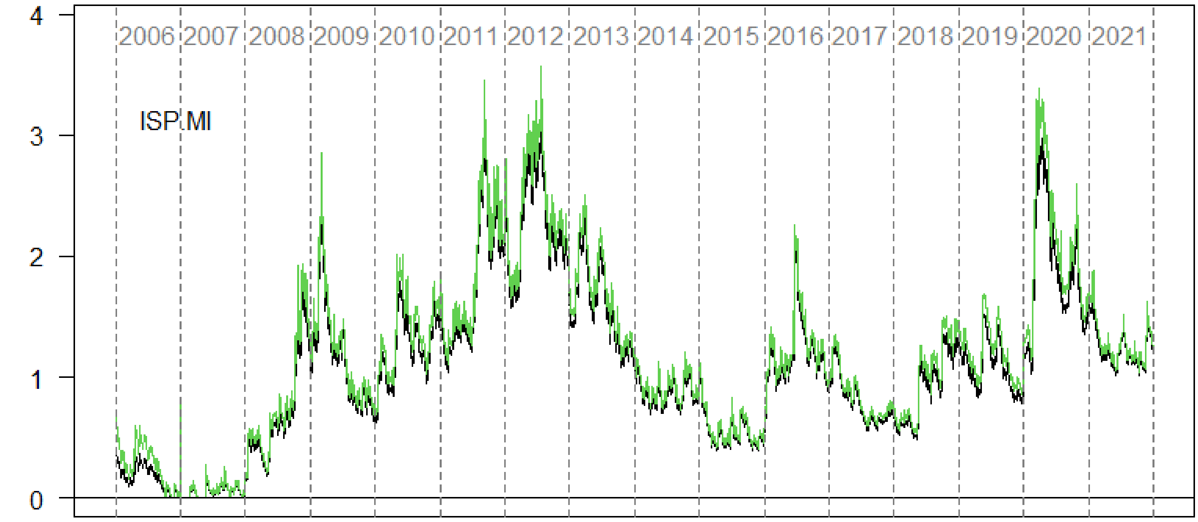
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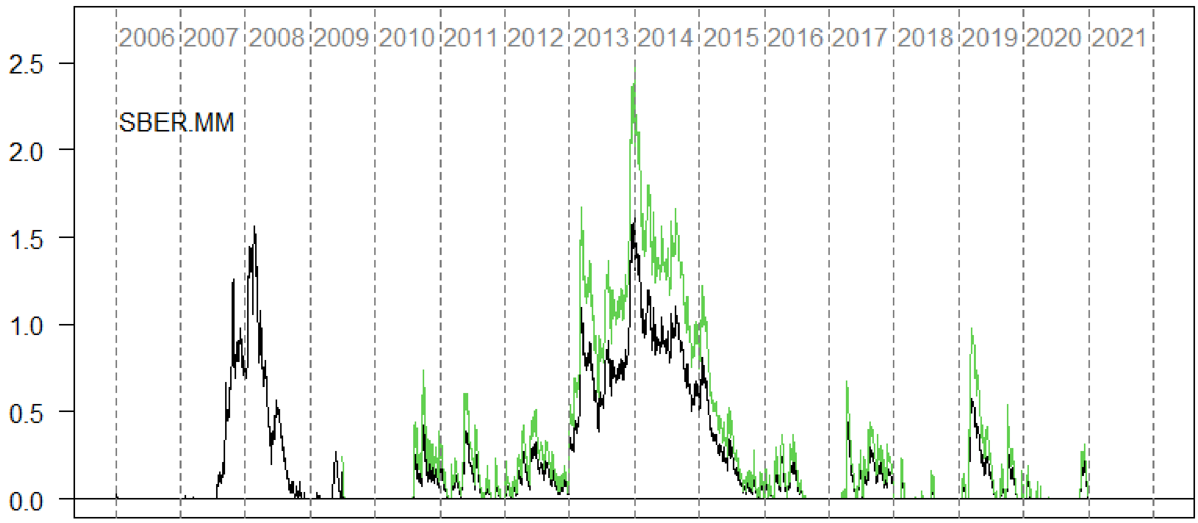
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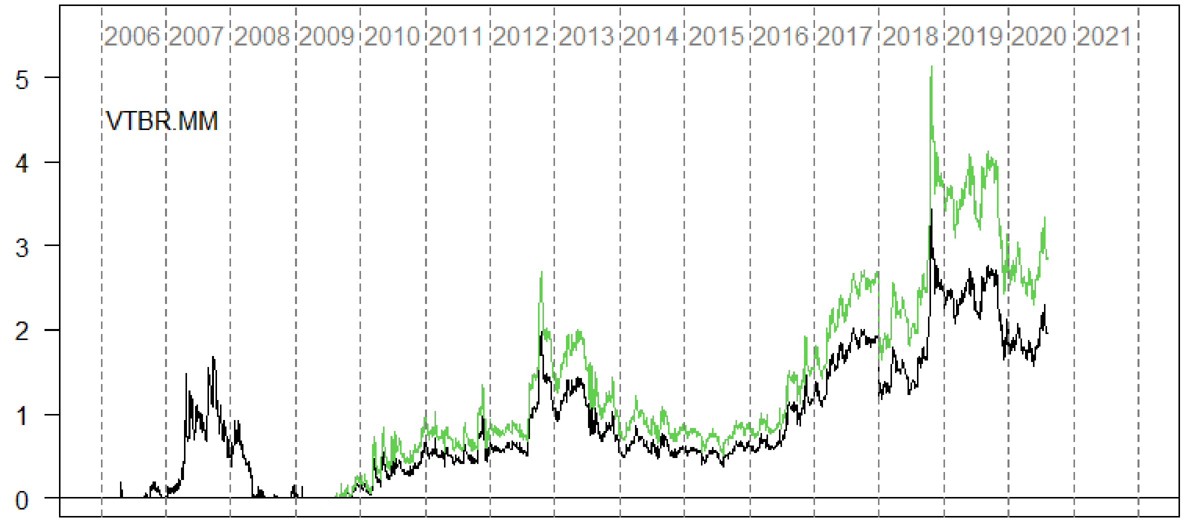

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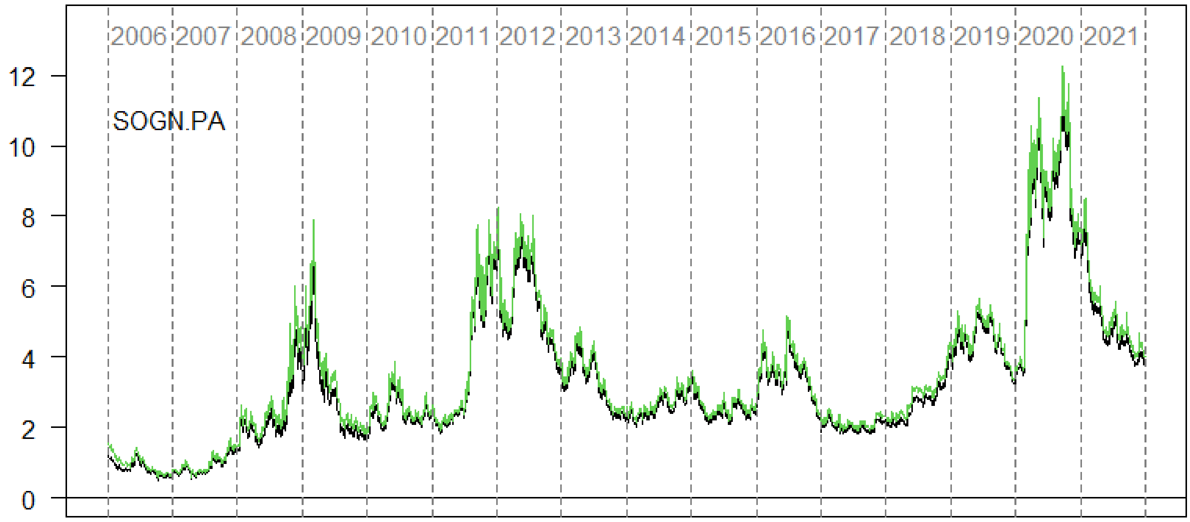

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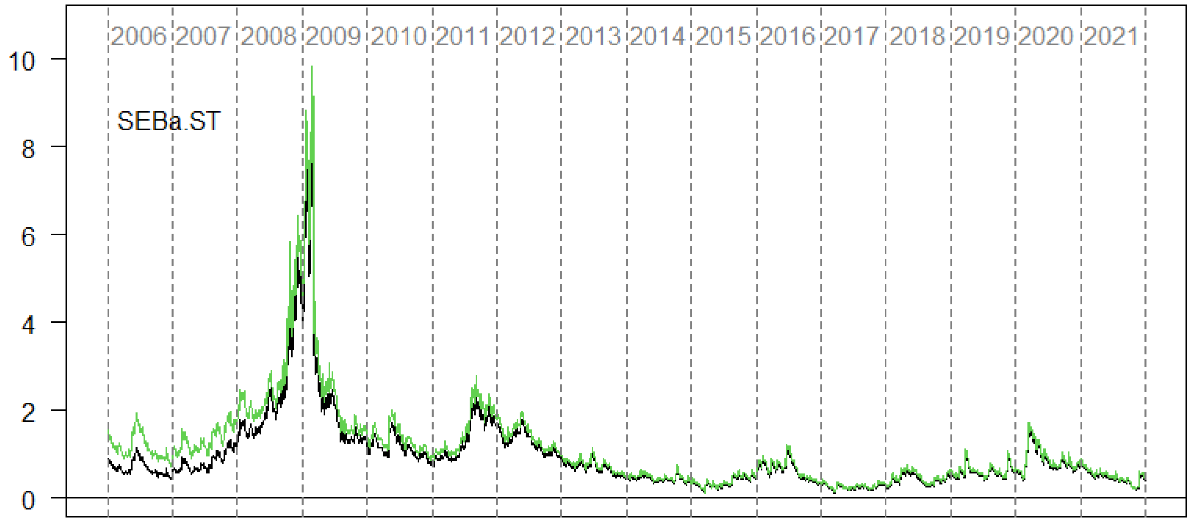

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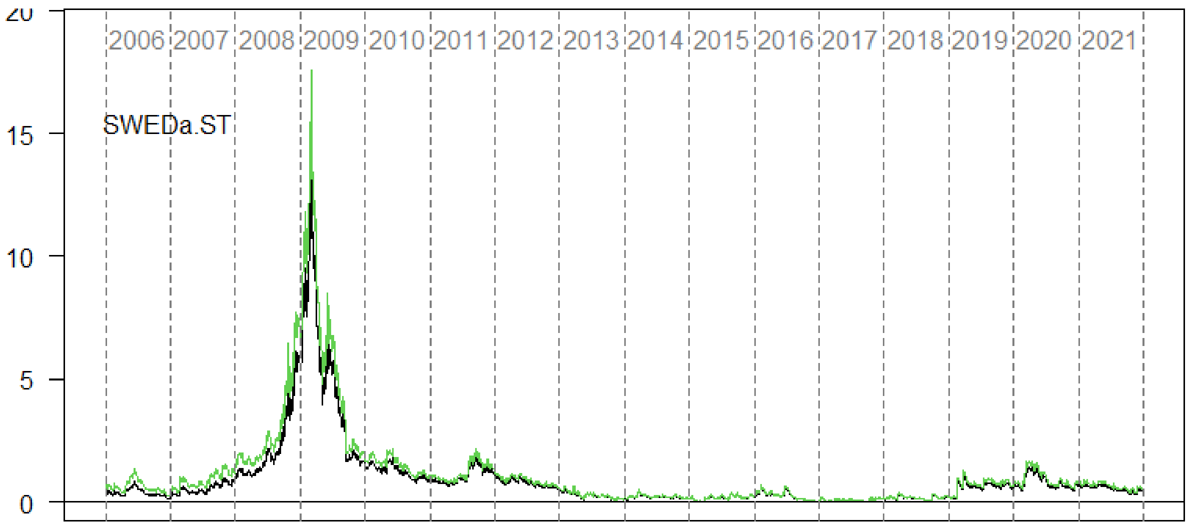
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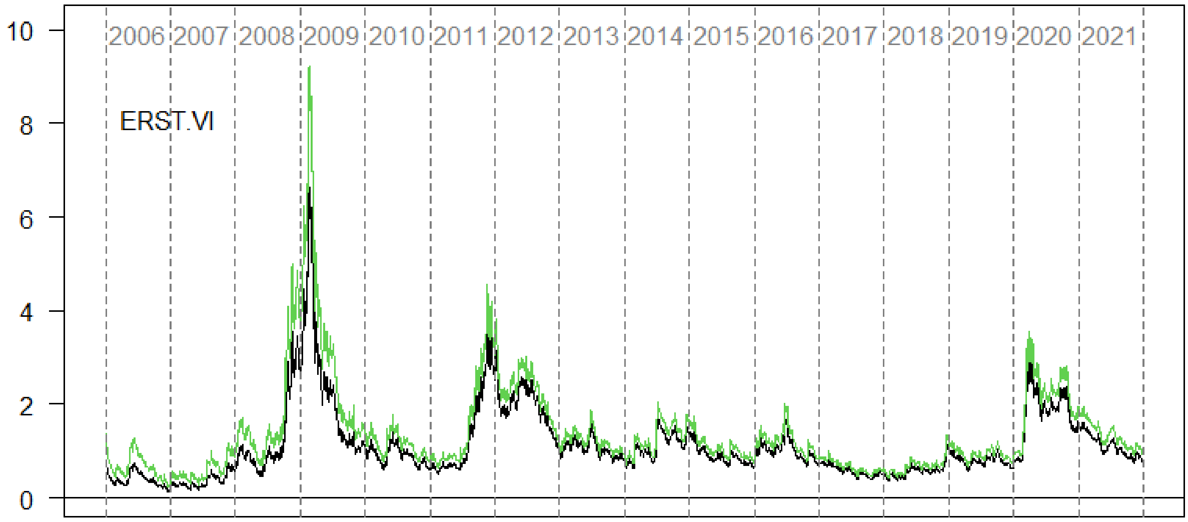
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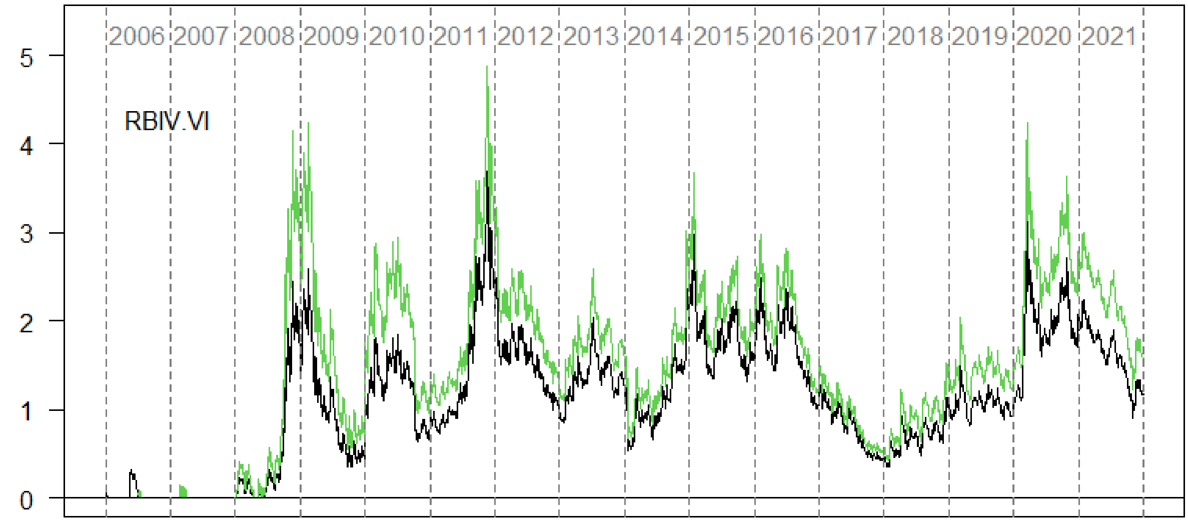
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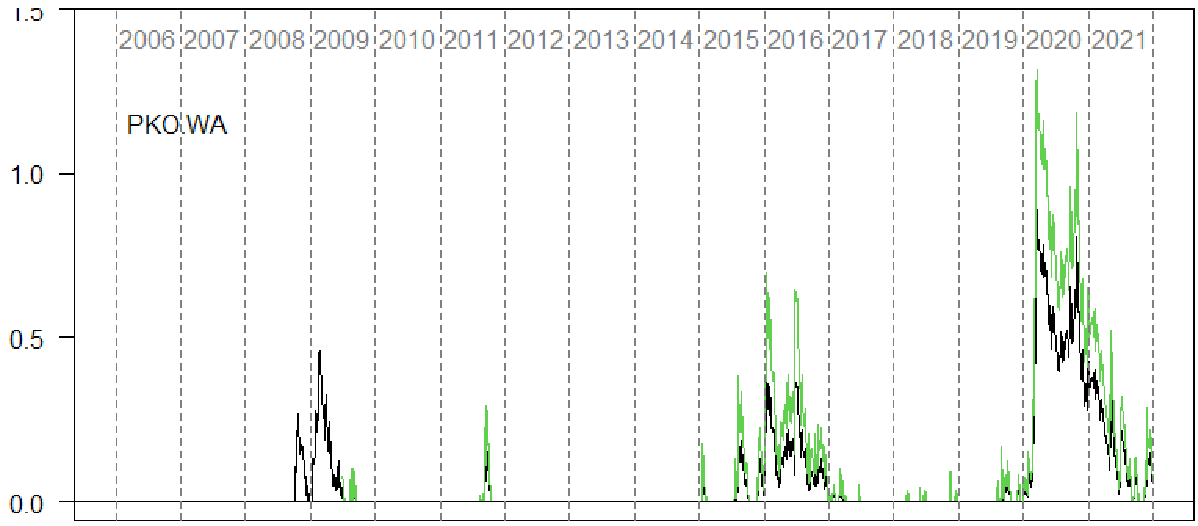
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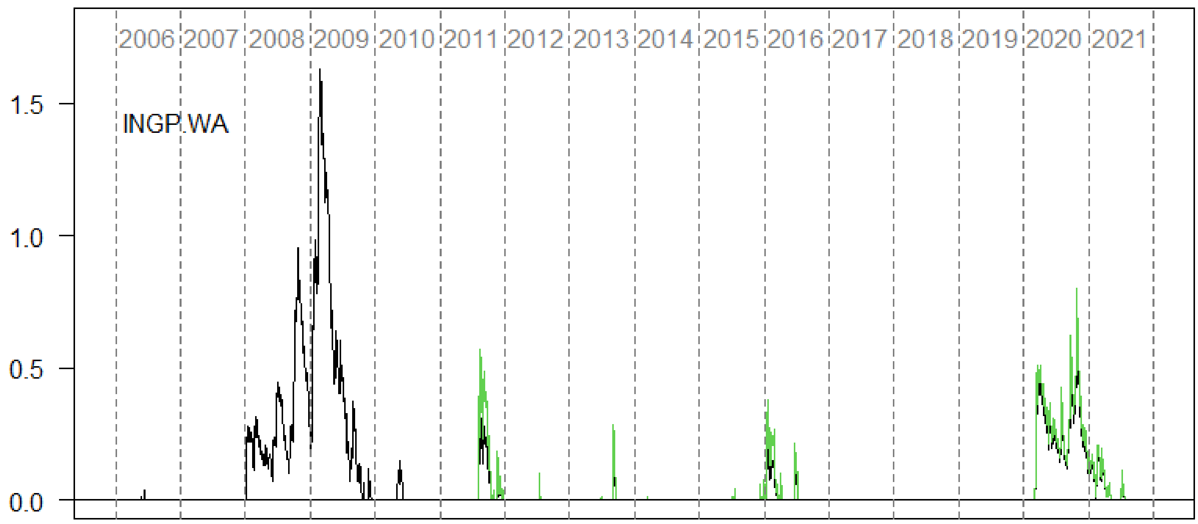
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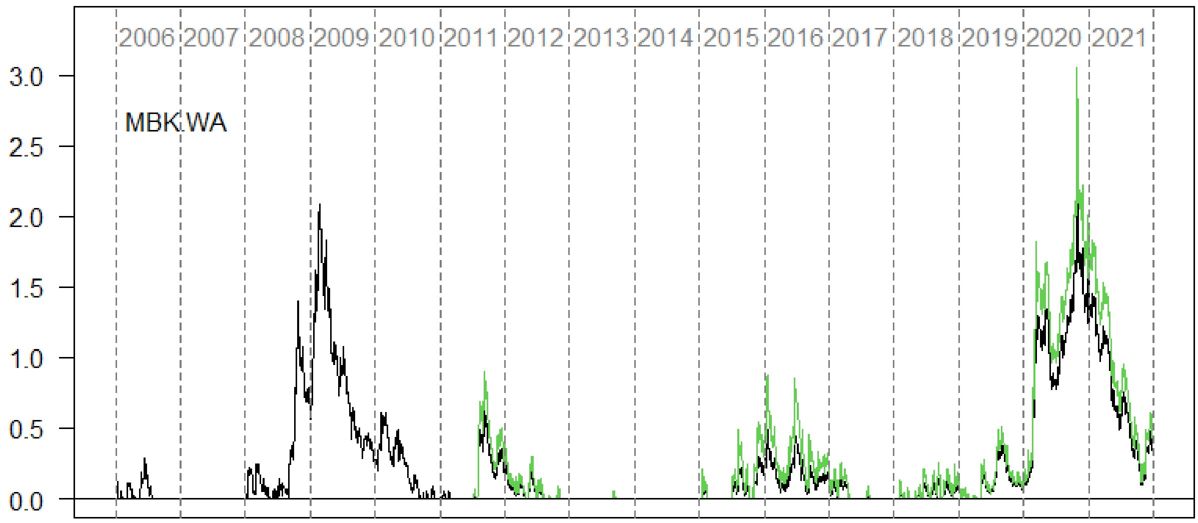
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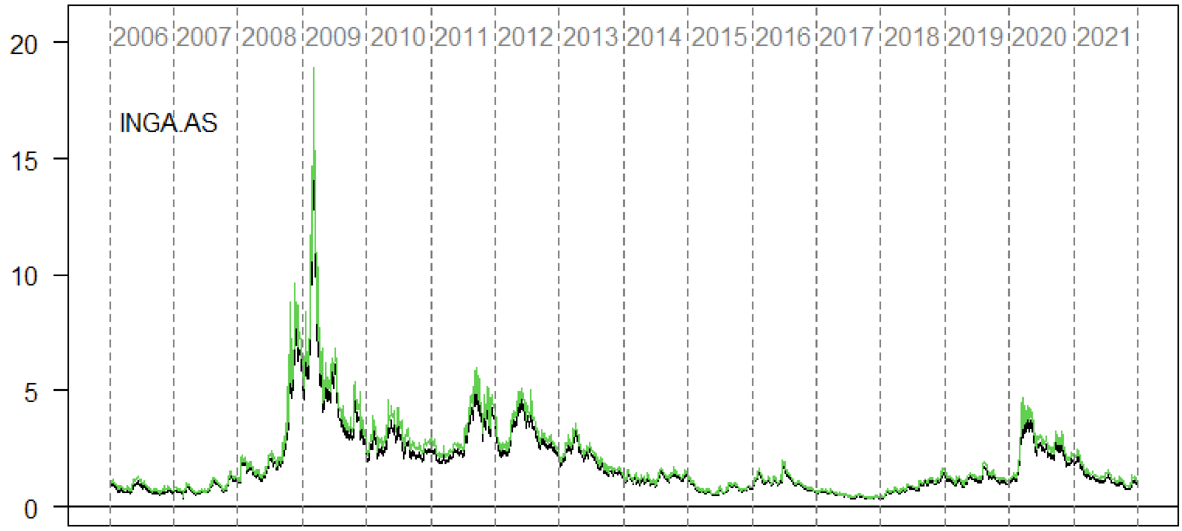

Table A1. List of analyzed banks and information about their systemic importance

Bank	Identifier	Base country	Systemic importance in the base country	Other countries where the bank is systemically important	Global SIFI (G-SIB)
Banca Transilvania S.A.	ROTLV.BX	Romania	YES		
Commerzbank AG.	CBKG.DE	Germany	YES		
Deutsche Bank AG.	DBKGn.DE	Germany	YES		YES
Erste Group Bank A.G.	ERST.VI	Austria	YES	2	
Eurobank Ergasias Srvcs and Hold SA	EURBr.AT	Greece	YES	2	
ING Bank Śląski S.A.	INGP.WA	Poland	YES		
ING Bank NV.	INGA.AS	Netherland	YES	3	YES
Intesa San Paolo S.p.A.	ISP.MI	Italy	YES	2	
KBC Group NV	KBC.BR	Brussels	YES	1	
mBank SA.	MBK.WA	Poland	YES		
OTP Bank Nyrt	OTPB.BU	Hungary	YES	2	
PKO BP SA.	PKO.WA	Poland	YES		
Raiffeisen Bank International A.G.	RBIV.VI	Austria	YES	4	
Sberbank	SBER.MM	Russia	YES		
Skandinaviska Enskilda Banken A.B.	SEBa.ST	Sweden	YES	3	
Société Générale S.A.	SOGN.PA	France	YES	1	YES
Swedbank A.B	SWEDa.ST	Sweden	YES	3	
UniCredit S.p.A.	CRDI.MI	Italy	YES	7	YES
VTB PAO	VTBR.MM	Russia	YES		

Table A2. Descriptive statistics of the SRISK(%) series (minimum, first quartile, median, mean, third quartile, maximum, standard deviation)

Bank	**Min**	**Q1**	**Median**	**Mean**	**Q3**	**Max**	**SD**
EURBr.AT	0.00	0.94	1.87	3.80	2.90	67.41	6.82

KBC.BR	0.00	0.25	0.48	1.04	1.44	12.38	1.34
OTPB.BU	0.00	0.00	0.00	0.09	0.15	0.79	0.14
ROTLV.BX	0.00	0.03	0.11	0.14	0.21	0.67	0.13
DBKGn.DE	1.00	3.07	3.92	4.25	5.29	16.06	1.83
CBKG.DE	1.32	2.46	3.73	4.60	5.70	32.20	3.51
CRDI.MI	0.21	1.22	1.71	2.04	2.73	8.75	1.17
ISP.MI	0.00	0.64	1.07	1.09	1.42	3.35	0.66
SBER.MM	0.00	0.00	0.08	0.22	0.26	1.64	0.32
VTBR.MM	0.00	0.53	0.73	1.05	1.62	3.44	0.71
SOGN.PA	0.51	2.08	2.73	3.29	4.15	11.73	1.99
SEBa.ST	0.09	0.46	0.68	0.93	1.13	8.53	0.88
SWEDa.ST	0.00	0.20	0.52	0.89	0.91	14.28	1.45
ERST.VI	0.13	0.65	0.90	1.10	1.26	6.63	0.76
RBIV.VI	0.00	0.72	1.16	1.16	1.64	3.70	0.68
PKO.WA	0.00	0.00	0.00	0.07	0.05	0.89	0.15
INGP.WA	0.00	0.00	0.00	0.03	0.00	0.72	0.09
MBK.WA	0.00	0.00	0.06	0.23	0.24	2.43	0.40
INGA.AS	0.32	0.83	1.24	1.82	2.39	17.08	1.54

Table A3. Descriptive statistics of the Environmental Pillar Score (minimum, first quartile, median, mean, third quartile, maximum, standard deviation)

Bank	**Min**	**Q1**	**Median**	**Mean**	**Q3**	**Max**	**SD**
EURBr.AT	36.04	62.56	69.66	67.23	72.08	85.30	12.85
KBC.BR	82.95	84.06	86.31	87.41	91.17	93.09	3.76
OTPB.BU	62.74	65.64	68.78	68.97	71.85	76.71	4.62
ROTLV.BX	2.42	2.79	30.34	36.54	64.08	83.08	40.46
DBKGn.DE	82.04	89.66	91.85	91.76	94.94	97.53	4.21
CBKG.DE	72.97	83.98	89.64	87.09	91.10	93.79	6.42
CRDI.MI	70.70	83.67	87.01	85.80	89.66	93.84	6.28
ISP.MI	35.10	88.48	92.83	87.78	94.03	97.01	14.74
SBER.MM	16.54	27.47	44.93	39.81	47.37	54.51	13.00
VTBR.MM	40.02	49.04	56.08	54.81	61.22	68.16	8.70
SOGN.PA	83.92	91.81	93.93	92.70	94.53	96.44	3.54
SEBa.ST	25.56	83.84	89.19	80.31	90.25	92.57	21.47
SWEDa.ST	25.47	79.26	82.57	76.15	87.12	88.44	19.25
ERST.VI	25.56	68.55	80.04	70.96	82.22	84.53	18.72
RBIV.VI	18.32	40.60	65.05	57.77	71.81	86.48	21.40
PKO.WA	15.30	16.78	18.32	27.72	48.15	51.05	15.43
INGP.WA	22.18	29.75	33.70	52.60	86.14	88.36	29.72
MBK.WA	8.27	15.48	28.34	39.81	64.62	75.29	27.09
INGA.AS	77.29	86.57	88.59	87.51	90.04	93.05	4.04

Table A4 Environmental Pillar Score-based ranking for five analyzed periods

Bank	2007-2009	2009-2013	2014-2019	2020-2021	2007-2021
Intesa San Paolo S.p.A.	89,93	92,70	91,47	97,01	92,26
Société Générale S.A.	88,40	94,40	94,21	93,22	92,25
Deutsche Bank A.G.	86,04	88,41	95,58	94,84	91,46

Commerzbank A.G.	89,68	91,20	86,77	91,06	89,06
UniCredit S.p.A.	87,18	88,54	86,23	93,84	88,13
Skandinaviska Enskilda Banken A.B.	83,78	87,30	89,64	90,17	87,70
KBC Group NV	86,95	86,51	88,74	89,70	85,18
Swedbank A.B.	74,74	84,36	85,23	81,76	82,50
ING Bank NV.	86,22	87,05	89,26	83,30	79,47
Erste Group Bank AG.	63,50	79,34	81,33	78,26	76,09
Eurobank Ergasias Srvcs & Hold SA	70,46	70,35	73,23	62,44	67,93
OTP Bank Nyrt	62,91	66,57	71,11	74,05	63,89
Raiffeisen Bank I.A.G.	32,39	62,92	72,89	63,11	62,22
VTB PAO	41,26	54,96	57,31	51,43	50,77
ING Bank Śląski S.A.	22,32	26,86	68,50	85,84	49,43
mBank S.A.	———	35,97	37,01	72,01	42,13
Sberbank	17,43	38,76	42,21	52,06	38,37
Banca Transilvania S.A.	———	———	21,03	83,08	37,08
PKO BP S.A	17,43	16,22	34,98	51,05	21,45
Different positions vs. E-SRISK-based ranking	14	4	6	16	17