Mathematical Finance

Master's Thesis

Volatility Spillovers among Environmental, Social and Governance Markets

Mariana Maia Silva

Supervision:
Prof. Adriana Cornea-Madeira

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Acronyms

ADF Augmented Dickey-Fuller.

AIC Akaike Information Criterion.

APEC Asia-Pacific Economic Cooperation.

ARCH Autoregressive Conditional Heteroskedasticity.

BIC Bayesian Information Criterion.

CDS Credit Default Swaps.

DY Diebold Yilmaz.

EAFE Europe, Australasia and Far East.

EM Emerging Markets.

ESG Environmental, Social and Governance.

GARCH Generalized Autoregressive Conditional Heteroskedasticity.

GDP Gross Domestic Product.

GFEVD Generalized Forecast Error Variance Decomposition.

LASSO Least Absolute Shrinkage and Selection Operator.

MA Moving Average.

MSCI Morgan Stanley Capital International.

P/BE Price-to-Book Equity Ratio.

P/E Price-to-Earnings Ratio.

USA United States of America.

VAR Vector Autoregression.

Abstract

This thesis investigates volatility spillovers across regional ESG equity markets using the Diebold and Yilmaz (2012) connectedness framework, based on generalized variance decompositions within a Vector Autoregression (VAR) framework. Focusing on the Morgan Stanley Capital International (MSCI) United States of America (USA), MSCI Europe, Australasia and Far East (EAFE), and MSCI Emerging Markets (EM) Extended Environmental, Social and Governance (ESG) Focus indices, from 2016 to 2024, the study quantifies total, directional, and net volatility spillovers among these regions. Volatility is estimated using a range-based approach and regularization techniques including Least Absolute Shrinkage and Selection Operator (LASSO) and Elastic Net which are employed to select the optimal lag length p of VAR model.

The findings reveal that a substantial share of total forecast error variance in volatility is attributable to spillovers. Additionally, the results confirm that spillover intensity is both time-varying and region-specific, particularly evident when total spillovers achieve its highest value, nearly by 60%, during globally synchronized ESG events, such as the COVID-19 pandemic, and appear more fragmented during regional crises.

Additionally, the EAFE Extended ESG Focus index acts as a net transmitter of volatility, while the USA Extended ESG Focus index gradually evolves into a persistent net receiver, contrary to what is typically observed in conventional financial markets. EM Extended ESG Focus index plays a more passive role in the spillover network, allowing for the assessment of how institutional and regulatory differences in developed and emerging markets shape volatility dynamics.

These results contribute to the literature by revealing differentiated volatility transmission mechanisms across ESG markets and offer practical insights for pricing models, risk management, and sustainable investment strategies.

Keywords: Volatility Spillovers; Diebold-Yilmaz Framework; Forecast Error Variance Decomposition; ESG Investing; Emerging Markets; Developed Markets; Sustainable Finance;

JEL Codes: C32; G11; G15; G18; G38; Q56.

Resumo

Esta dissertação investiga os efeitos de transmissão de volatilidade entre mercados regionais de ações ESG, recorrendo à metodologia proposta por Diebold e Yilmaz (2012), baseado na decomposição generalizada da variância dos erros de previsão no âmbito de um modelo VAR. A amostra inclui os índices MSCI USA, MSCI EAFE e MSCI Emerging Markets Extended ESG Focus, no período entre 2016 e 2024, permitindo quantificar os spillovers de volatilidade totais, direcionais e líquidos entre estas regiões. A volatilidade é estimada através de uma abordagem com base na amplitude dos preços, sendo a ordem ótima do modelo VAR selecionada com recurso a técnicas de regularização como o LASSO e o Elastic Net.

Os resultados revelam que uma proporção significativa da variância total dos erros de previsão da volatilidade se deve a efeitos de spillover. Confirma-se ainda que a intensidade da transmissão é variável no tempo e dependente da região, particularmente visível quando atinge o seu valor máximo, próximo de 60%, durante eventos ESG globais, como a pandemia da COVID-19, apresentando-se mais fragmentada em episódios de crise regional.

O índice EAFE atua como principal transmissor de choques de volatilidade, enquanto o índice dos EUA evolui para uma posição de recetor persistente, contrariando a evidência existente na literatura referente aos mercados financeiros convencionais. Por outro lado, o índice dos mercados emergentes revela um comportamento mais passivo, refletindo, possivelmente, estruturas regulatórias ESG menos desenvolvidas e menor integração nos mercados financeiros globais. A distinção entre mercados desenvolvidos e emergentes é considerada de forma explícita, permitindo avaliar de que forma diferenças institucionais e regulamentares influenciam a dinâmica da transmissão da volatilidade.

Este estudo contribui para a literatura ao evidenciar mecanismos diferenciados de propagação da volatilidade em mercados ESG e oferece implicações relevantes para a construção de modelos de valorização, estratégias de gestão de risco e decisões de investimento sustentável.

Palavras-Chave: Transmissão de Volatilidade; Metodologia de Diebold-Yilmaz; Decomposição da Variância do Erro de Previsão; Investimento ESG; Mercados Emergentes; Mercados Desenvolvidos; Finanças Sustentáveis;

Códigos JEL: C32; G11; G15; G18; G38; Q56.

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1 Introduction

Markets are in constant motion, driven by a range of expectations, information flows, and reactions that make the financial system inherently complex. Due to its dynamic nature, disruptions in one financial market hardly remain isolated, rippling through asset classes, sectors, and geographies. This phenomenon, known as volatility spillovers, has become a central concern for investors, regulators, and risk managers. In an increasingly interconnected global financial system, identifying these pathways of risk transmission is vital for building investment strategies and developing market risk assessment models.

This research was developed during my internship at KPMG Portugal, particularly in the Financial Services - Risk Consulting department, where I was integrated into a team working on the validation and ongoing monitoring of pricing models for a wide range of financial instruments. A critical part of the work was identifying discrepancies between theoretical model behavior and real-world market conditions, then proposing improvements to ensure greater accuracy and compliance with regulatory standards. Being part of this project made me aware of how financial instruments are interdependent: isolated shocks, such as sudden changes in implied volatility or inconsistent calibration, can propagate through a broader portfolio, altering its overall risk characteristics.

Simultaneously, I found myself more exposed to discussions around sustainability and ESG practices - not merely as a corporate buzzword, but as a significant shift on how risk and value are perceived. Together, the combination of these reflections culminated in a key question: if such effects occur at the model level, how do volatility shocks spreads across entire ESG markets or indices? This report is my attempt to explore how volatility spillovers behave in a sustainability-focused context. Using the Diebold and Yilmaz (2012) methodology, I examine volatility transmission across three ESG equities.

The structure of the dissertation is as follows. Section 2 outlines relevant empirical studies on this thematic. In Section 3, I describe the dataset, justifying each step of the process which includes the selection of the ESG stock market indices and volatility estimation. Section 4 details the Diebold and Yilmaz (2012) methodology and the regularization techniques used to select the most relevant variables. Section 5 presents the results. Finally, the dissertation concludes with reflections on the findings, limitations and potential avenues for further research.

2 Literature Review

The volatility spillovers have been central to understanding systemic risk and financial interdependence. As the globalization and integration of financial markets rises, localized shocks have now more far-reaching implications. One of the most widely used tools to assess connectedness and transmission effects in financial markets is the Diebold and Yilmaz (2009, 2012) framework.

Following research focuses on the application of the model within equity markets in various regional integration scenarios. Yilmaz (2010) explores the degree of interconnectedness and transmission effects across East Asian equity markets. Diebold and Yilmaz (2011) provide an empirical analysis of return and volatility spillovers among five stock markets in Americas: Argentina, Brazil, Chile, Mexico, and the United States. Similarly, Kakran et al. (2023) analyzes interconnection across Asia-Pacific Economic Cooperation (APEC) countries, robustly reinforcing the argument that regional integration contributes to stronger financial linkages and spillover intensities among member economies. Building on these applications within financial markets, Diebold and Yilmaz (2015) extend their earlier framework into a new domain: connectedness over the business cycle. Unlike previous studies, this research marks a turning point in the connectedness literature by shifting the focus from financial market spillovers to real economic activity. By analyzing Gross Domestic Product (GDP) connectedness across six developed economies over nearly five decades, they introduce the concept of output spillovers as inherently time-varying and cyclical in nature.

Additional studies use this conceptual foundation to explore connectedness in economies and financial institutions during different phases of the global business cycle (Diebold and Yilmaz, 2016; Uluceviz and Yilmaz, 2018; Demirer et al., 2018). The findings consistently reveal particular stronger volatility spillovers and bilateral relationships in times of financial stress such as the global crisis in 2007-2008 and the massive deterioration on the health of European Union financial institutions in mid-2011. Demirer and Yilmaz (2015) find that equity connectedness among the world's largest financial institutions increases notably during crises, with cross-country linkages playing a dominant role. With the same purpose, Korobilis and Yilmaz (2018) estimate a large Bayesian time-varying parameter vector autoregressive (TVP-VAR) model of daily stock return volatilities, showing that it captures the intensification of jumps and tensions more accurately than the rolling-windows based in Diebold and Yilmaz Connectedness Index.

Contributing literature can also be found in more recent applications across the banking system and credit risk instruments. Bostanci and Yilmaz (2020) investigate the global network structure of sovereign credit risk using Credit Default Swaps (CDS). Notably, their findings underscore not only the versatility of Diebold and Yilmaz framework, but also its relevance in evaluating the complex network of connections that characterize modern financial systems.

One particular interesting paper is developed by Anghel and Caraiani (2025), which introduces a novel perspective by moving beyond traditional quantitative measures: investor sentiment. In other words, the authors demonstrate that the way people feel about the market can propagate from one financial institution to another, significantly impacting financial stability. As so, they distinguish between two key dimensions of sentiment-driven risk: type of investor sentiment - positive and negative - and the channel of transmission - direct, through clear institutional linkages, and indirect, via herding behavior. The findings show that directly transmitted optimist can help create stability, whereas pessimism communicated indirectly often leads to greater vulnerability within the system. Overall, this behavioral dimension adds a new layer to the understanding of volatility transmission, reinforcing that emotions and perception can significantly amplify systemic risk.

Despite the growing body of literature on spillovers, relatively few studies have focused specifically on volatility transmission within ESG-indexed equities. Over the past few years, the discussion surrounded ESG considerations has expanded from their firm-level performance to their broader implications into ESG investment decision-making (Capelli et al., 2021; Gavrilakis and Floros, 2023; Yin et al., 2023; Berk et al., 2023; Guo et al., 2023; Suprihadi and Danila, 2024; Bhandari et al., 2024). However, much of the existing literature tends to treat ESG as a unified or static category, without accounting for the evolving regulatory and macroeconomic divergences across regions.

This study contributes to address this gap by examining ESG volatility spillovers across global regions, thereby enriching the literature on systemic risk in sustainable investing. Researchers in this field began to explore related questions. Shaik and Rehman (2023) and Karkowska and Urjasz (2025) focus on regional spillovers and compare developed and emerging ESG markets by investigating dynamic volatility connectedness across different ESG stock market indices. The results reveal some differences among the two studies: Shaik and Rehman (2023) find that Middle East Africa and Latin America are net transmitters, while the United States and Asia Pacific are net receivers; Karkowska and Urjasz (2025) employ an additional comparison between conventional and ESG-focused stock market indices, aiming to assess whether the inclusion of ESG factors changes the dynamics of volatility spillovers. The findings from conventional indices indicate that North American and developed European markets are shock transmitters, while emerging European and Asia-Pacific economies act as the main receivers. By incorporating ESG factors, emerging European markets become a transmitter, and Latin America transits into a receiver.

Moosawi and Segerhammar (2022) explore different country-level ESG leader indices and expand the scope of the analysis by integrating commodity, currency, and global benchmark indices. By incorporating these additional asset classes, the authors aim to assess how ESG assets interact with key macro-financial variables, particularly under conditions of market stress. The results hold consistently across both return-based and volatility-based analysis, revealing that country-level ESG indices exhibit stronger integration with one another than with traditional asset classes, and tend to act as net transmitters towards global benchmarks, commodities and currency rates. More importantly, the study suggests that ESG indices can reduce exposure to external shocks, reinforcing the relevance of ESG assets as tools to manage systemic risk and improve diversification.

Asih et al. (2024) makes an additional effort to the contributing ESG spillover literature, examining volatility connectedness across various Indonesian companies segmented by categories according to their ESG score. This study shifts the focus from aggregated ESG indices to firm-level heterogeneity, assessing how the ESG performance itself shapes market connectedness. Findings indicate that companies with lowest ESG performance exhibit high levels of volatility yet low spillover connectedness with both domestic and global markets, suggesting that their risk profile is largely idiosyncratic, driven by firm-specific factors rather than broader market determinants. Contrarily, companies with higher ESG scores show stronger linkages to both indices, indicating greater exposure to systematic risk.

This study offers a contribution to an emerging but still relatively limited strand of research that focuses on sustainable investing. While some of the existing literature have provided important insights, many rely on combinations of indices from different providers (Karkowska and Urjasz, 2025) or blend diverse asset classes (Moosawi and Segerhammar, 2022) within a single network. As so, this research attempts to address these limitations by going more in-depth into regional dynamics and comparisons within developed and emerging markets. Specifically, I aim to provide a detailed analysis of how economic shocks impact volatility spillovers across ESG equities by focusing exclusively on three regionally segmented indices.

This approach is particularly relevant given that ESG markets across regions are shaped by fundamentally different drivers: ESG performance in developed economies is often driven by well-established regulatory systems, institutional investor norms and advanced disclosure practices, while emerging markets are often characterized by fragmented ESG adoption, weaker enforcement, and greater exposure to idiosyncratic shocks. These differences may suggest that volatility in ESG assets may not only vary in magnitude across regions, but also behave differently in terms of persistence and transmission. As such, adopting a regional perspective is essential to avoid misleading generalizations about ESG resilience or contagion.

3 Dataset Organization

This chapter presents the empirical foundation of the study, detailing the data sources, the construction of variables, and the methods used to prepare the dataset for subsequent modeling. It starts by outlining the data collection process and giving a brief description of the select indices, highlighting their geographical and market characteristics. This is followed by the introduction of the methodology used to estimate daily volatility and the respective summary statistics, distributional features, and time-series dynamics.

3.1 Data Collection

The data is based on the collection of daily stock price data from three ESG equity market indices - MSCI USA Extended ESG Focus, MSCI EAFE Extended ESG Focus and MSCI EM Extended ESG Focus - whose details are summarized in Table I. The original sample consisted of 2307 trading days, which was reduced by 26% after applying a listwise deletion approach using `na.omit()` in R Studio.

The missing values in the dataset are largely explained by differences in trading calendars across the selected markets. For example, U.S. markets close on days such as Thanksgiving or Independence Day, while exchanges in Asia or Europe remain open. Conversely, markets like Japan close during Golden Week, and China during the Lunar New Year, even when the U.S. is trading. In addition, there are global holidays, such as Christmas Day and New Year's Day, when virtually all major markets are closed.

In order to mitigate excessive data loss while preserving the temporal structure required by Diebold and Yilmaz (2012) methodology, linear interpolation was used to address brief stretches of missing data (You et al., 2024). Specifically, short gaps in the data (no more than two days in a row) were completed using this method. This approach kept approximately 75% of the available data intact while preventing unnatural fluctuations in volatility.

Table I: Data Description

Index	Time Period
MSCI USA Extended ESG Focus	01/01/2016 - 31/12/2024
MSCI EAFE Extended ESG Focus	04/01/2016 - 31/12/2024
MSCI EM Extended ESG Focus	04/01/2016 - 31/12/2024

Source: Thomson-Reuters

3.2 Morgan Stanley Capital International Extended Environmental, Social and Governance Focus Indices

The selection of the three MSCI Extended ESG Focus Indices was guided by two core principles: comparability and interpretability. From a comparability point of view, all indices are constructed under the same MSCI's Extended ESG Focus methodology, which applies a consistent set of ESG selection and weighting criteria across regions. This consistent approach guarantees that any observed differences in volatility spillovers arise from regional market dynamics and not from inconsistencies in the index's design.

Besides that, the decision to limit the system to three variables, each representing a distinct economic and geographic block, was made in order to ensure interpretability. Although the Diebold and Yilmaz (2012) connectedness framework allows higher dimensional systems, expanding the number of variables often leads to model complexity and statistical stability, particularly in rolling-window settings or with limited sample sizes.

From a storytelling standpoint, focusing on three distinct regions allows for the creation of a straightforward and understandable narrative about how ESG-related volatility is transmitted across different tiers of market development. This approach enables to clearly distinguish between net transmitters and receivers of volatility, to observe time-varying spillover patterns, and to relate those patterns to economic events or ESG-policy shifts, without the risk of the analysis becoming ambiguous or fragmented.

Having explained the choice of the explanatory variables, this subchapter aims to provide a contextual background about them in terms of market size, geographical distribution, and structural characteristics. Additionally, appendices A.1, A.2 and A.3 offer a detailed composition data for each index, including sector and country weights, as well as the 10 top constituents by index weight to give a more comprehensive understanding of their underlying structure. According to MSCI Inc. (2025), the MSCI Extended ESG Focus Indices are defined as follows.

> The MSCI Extended ESG Focus Indexes (the 'Indexes') are designed to maximize their exposure to positive environmental, social and governance (ESG) factors while exhibiting risk and return characteristics similar to those of the underlying market capitalization weighted index. The Indexes are constructed by selecting constituents of a market capitalization weighted index (the 'Parent Index') through an optimization process that aims to maximize exposure to ESG factors for a target tracking error budget under certain constraints. The Indexes are sector-diversified and target companies with high ESG Ratings. Companies with exposure to Tobacco, Controversial Weapons, Civilian Firearms, Oil Sands and Thermal Coal are not eligible for inclusion in the Indexes.
>
> In: MSCI Inc. (2025), p. 3.

Table II offers a side-by-side comparison of the three indices, evaluating their positioning regarding market size and value. Geographically, the MSCI USA Index encompasses large- and mid-cap US equities, while the EAFE Index represents advanced markets outside of North America, particularly in Europe, Australasia and Far East. The EM Index includes developing nations across various countries, particularly, in China, Taiwan, and India. This geographical breakdown illustrates unique market behaviors, levels of economic advancement, and approaches to environmental, social, and governance principles, appealing to investors who prioritize sustainability.

Table II: Comparative Overview of MSCI Extended ESG Focus Indices

Index	Composition	Market Cap	P/E	P/BE	ESG Score
MSCI USA	285	\$39.86 T	25.15	4.81	7.4
MSCI EAFE	374	\$13.61 T	15.44	1.91	8.5
MSCI EM	281	\$5.04 T	15.53	1.68	7.4

Starting by assessing the market size of each index, although the MSCI EAFE holds the greatest number of constituents, reflecting a wide broad diversification, the largest overall market capitalization belongs to MSCI USA, underscoring the size and dominance of American firms. Conversely, the MSCI EM, centered in emerging markets, exhibits the least overall market capitalization, aligning with the generally smaller and less established character of these markets.

The evaluation of market valuation was based on the analysis of two key financial metrics - the Price-to-Earnings Ratio (P/E) and Price-to-Book Equity Ratio (P/BE) ratios - which reflects the investors' expectations regarding a company's future profitability and the market's valuation of its net assets, respectively. Among the three indices, MSCI USA outperforms both P/E and P/BE ratios, suggesting a strong desire from investors to invest more in companies that have significant worth in non-physical assets—such as brand strength, intellectual property, or digital resources. This aligns with the structure of the USA market, which is largely focused on technology and service-based industries. The MSCI EAFE and MSCI EM show relatively similar lower ratios, indicating a more cautious approach towards political, regulatory, and currency-related risks.

Concerning ESG performance, MSCI EAFE stands out presenting the highest ESG score, indicating that developed economies beyond North America, especially Europe and Asia-Pacific regions, display relatively better ESG practices. This is probably a result of tougher regulatory frameworks, more advanced corporate transparency requirements, and increased demands from stakeholders for sustainable business polices.

3.3 Volatility Estimation

Volatility can be computed in various ways using different methodologies. A straightforward approach consists of measuring the standard deviation of past returns, which operates under the assumption of constant volatility during the estimation period (David E. Allen and Singh, 2016).

As so, some empirical studies (Yu Ying and Yi, 2020; Moosawi and Segerhammar, 2022; Shaik and Rehman, 2023) use time-series models such as the Autoregressive Conditional Heteroskedasticity (ARCH) model introduced by Engle (1982), and its extension, the Generalized Autoregressive Conditional Heteroskedasticity (GARCH) model developed by Bollerslev (1986) in order to capture the dynamic nature of financial markets and overcome the limitation of using constant volatility.

Additionally, when high-frequency intraday data is available, realized volatility estimators have become a widely adopted alternative in the literature (Andersen and Bollerslev, 1998). These approaches compute daily volatility by summing squared intraday returns, typically at 5 or 10-minute intervals, thus capturing more granular movements in market activity. This method allows for a non-parametric and model-free estimation of volatility that can better reflect micro-structural dynamics and volatility clustering.

Besides return-based models, volatility can also be estimated by using price range data, which utilizes the high, low, opening, and closing prices during a trading day. For this particular study, I have chosen to estimate the daily return volatility for the MSCI Extended ESG Focus Indices adopting precisely a range-based volatility estimator that integrates the approaches of Garman and Klass (1980) and Alizadeh et al. (2002).

The starting point is the Garman and Klass (1980) estimator, which improves upon traditional close-to-close volatility by using open, high, low and close prices from each trading day. It assumes zero drift and no overnight jumps. The original formula is as follows:

$$\sigma^2_{GK,t} = 0.5\left(\ln\left(\frac{H_t}{L_t}\right)\right)^2 - (2\ln(2)-1)\left(\ln\left(\frac{C_t}{O_t}\right)\right)^2 \tag{1}$$

where H_t, L_t, O_t and C_t are the high, low, open, and close prices, respectively.

This approach improves effectiveness in normal market conditions, yet it fails to consider sudden changes or other complexities that often occur in real markets. Since the focus of this research is to analyze volatility spillover effects across different regional markets, capturing volatility behavior during times of stressed market conditions is inherent to the analysis. As so, in order to overcome this limitation, I have decided to incorporate an extension of the previous estimator through the Alizadeh et al. (2002) estimation, who propose the application of logarithmic price range, given by the following expression:

$$\sigma_{A,t} = \ln(H_t) - \ln(L_t) \tag{2}$$

where H_t and L_t are the high and low prices, respectively.

This log-range estimator allows for a more accurate estimation of daily volatility by incorporating a complete spectrum of intraday price fluctuations, including sudden jumps and asymmetric behaviors, which are critical for accurately identifying cross-market transmission dynamics during periods of financial crises.

Therefore, following the approach in Demirer and Yilmaz (2015), which integrates and extends the volatility estimators of Garman and Klass (1980) and Alizadeh et al. (2002), the final estimator I have decided to use is entirely expressed in log-price terms, as follows:

$$\begin{aligned}\tilde{\sigma}^2_{4,t} = 0.511(H_t - L_t)^2 - 0.019\,[(C_t - O_t)(H_t + L_t - 2O_t)] \\ - 2(H_t - O_t)(L_t - O_t) - 0.383(C_t - O_t)^2\end{aligned} \tag{3}$$

where H_t, L_t, O_t e C_t denote the same designations as in (1).

3.4 Descriptive Analysis of Volatility across Indices

Having detailed the construction of the volatility estimator, it is now appropriate to provide a summary of the data employed in the analysis. Alongside the key economic metrics presented in subsection 3.2, Table III displays additional descriptive statistics in order to describe the behavior of daily volatility for the three major indices and support more informed investment decisions through a multidimensional view of each index.

Table III: Descriptive Statitics of Daily Volatility of MSCI Extended ESG Focus Indices

Index	Mean	St. Dev	Min	Max	Skewness	Kurtosis
MSCI USA	0.0091	0.0068	0.0000	0.0709	2.96	15.34
MSCI EAFE	0.0081	0.0049	0.0000	0.0691	3.44	24.52
MSCI EM	0.0074	0.0040	0.0005	0.0579	3.28	25.28

All three markets exhibit positive average daily volatility, where the USA market shows the highest mean volatility. The variations in volatility are clearly biased to the right, indicating that although low or moderate volatility occurs frequently, there are sporadic days of significantly heightened volatility. This pattern is illustrated through the histogram displayed in Figure 1, whose asymmetry reflects the impact of rare but substantial shocks, such as ESG-related international events, geopolitical tensions or sudden changes in investor sentiment.

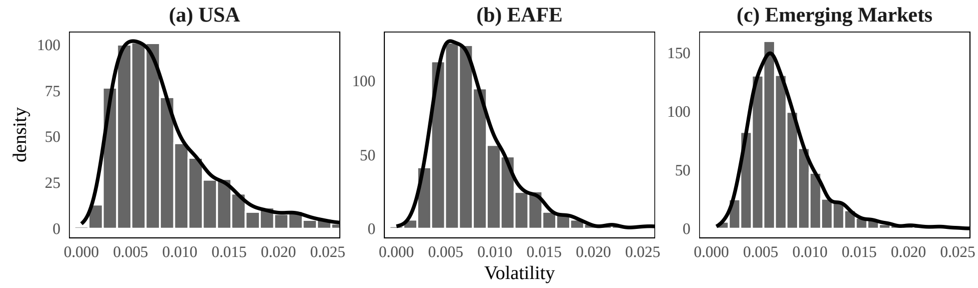

Figure 1: Histogram for three MSCI Extended ESG Focus Indices.

While summary statistics provide a useful insight about the overall distribution and skewness of volatility, they fail to capture the temporal dimension or identify particular episodes that leads to extreme values. To complement this information, Figure 2 illustrates a time-series plot of daily volatility across the three market indices from 2018 to early 2024.

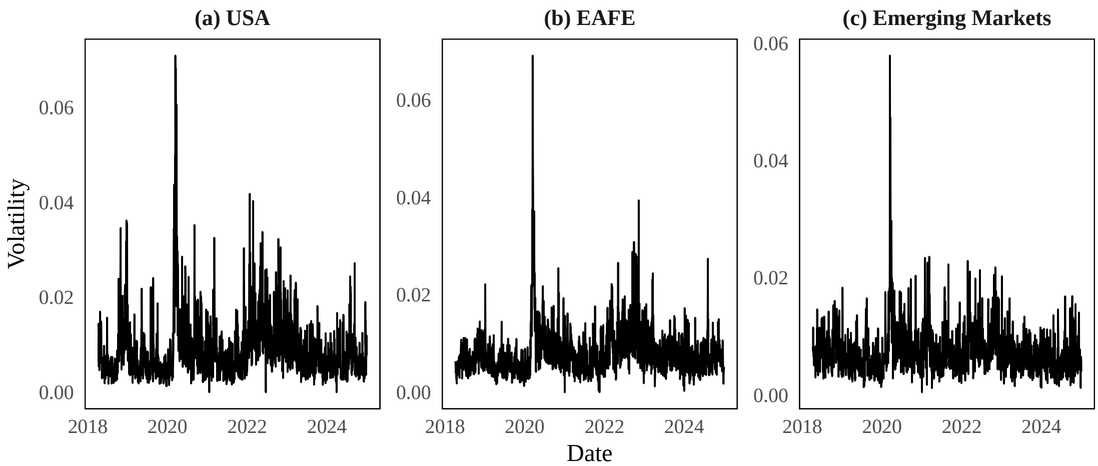

Figure 2: Daily Volatility of MSCI Extended ESG Focus Indices.

The volatility spikes across USA, EAFE and EM are mainly influenced by common global shocks, although the magnitude and persistence differ by region. The most evident spike occurs in early 2020, corresponding with the beginning of the COVID-19 outbreak, which led to severe stress in financial markets globally. This simultaneous increase in volatility indicates the greater uncertainty caused by widespread lock-downs, significant economic disruptions, and the initial absence of a coordinated policy response. Although the shock was felt worldwide, the USA and EAFE markets demonstrated particularly significant volatility, probably due to their strong connections to international financial systems and the sudden decline in investor confidence.

A second major surge in volatility is observed around early 2022, particularly in the EAFE and EM, and is likely associated with the Russia-Ukraine war. The MSCI EAFE was particularly affected by this conflict due to the high reliance of some European markets on Russian energy imports. In the subsequent period, volatility spikes, especially in USA, are likely related to the US The Federal Reserve's significant increases in interest rates in response to growing inflation.

4 Methodology

Recently, the interconnectedness of financial markets has been a widely commented topic in the analysis of systemic risk, contagion, and volatility transmission. A commonly used method for assessing these linkages is the Connectedness Framework proposed by Diebold and Yilmaz (2012). This approach offers a precise and easily understandable means to evaluate how disruptions in one asset or market affect the prediction error variance of others, utilizing variance decompositions obtained from VAR models. Formally, the system is modeled using a VAR of order p, given by:

$$\mathbf{y}_t = \sum_{i=1}^{p} \Phi_i \mathbf{y}_{t-i} + \varepsilon_t \tag{4}$$

where $\mathbf{y}_t$ is an $N \times 1$ vector of endogenous variables, Φ_i are $N \times N$ coefficient matrices for each lag i and $\varepsilon_t \sim \mathcal{N}(0, V)$ is a vector of white noise innovations with zero mean and variance-covariance matrix V.

For this particular study, I began by estimating the VAR model where $\mathbf{y}_t = [\sigma_t^{USA}, \sigma_t^{EAFE}, \sigma_t^{EM}]'$ is the vector of daily volatilities of the MSCI USA, EAFE, and EM ESG Extended Focus Indices, respectively. Although the VAR system in this study includes only these three variables, the estimation is carried out using a rolling-window approach, where the model is re-estimated repeatedly over subsets of the full sample. This method is necessary to capture time-varying spillover dynamics, but it comes with a trade-off: each window contains fewer observations than the full dataset, effectively reducing the sample size available for estimation at each point in time.

In this context, choosing an appropriate lag order p for the VAR model becomes particularly important. If p is too low, the model may miss important temporal relationship, failing to capture how past values influence current dynamics. Conversely, if p is too high the model includes a large number of lagged terms that may not meaningfully contribute to prediction and increases the inefficiency of the estimates. Given the use of daily data over a five-year period and the inclusion of only three variables, it was essential to find a balance between capturing relevant dynamics and maintaining a parsimonious model.

Traditionally, researchers rely on lag selection procedures based on information criteria such as the Akaike Information Criterion (AIC) and the Bayesian Information Criterion (BIC). Although these methods are widely accepted and theoretically well-grounded, their application would result in re-estimations of the VAR model across hundreds of overlapping windows and evaluating multiple lag structures within each window, making the process computationally intensive and inefficient. More importantly, the selected lag order p could vary from window to window, introducing inconsistency into the connectedness estimates.

To address these limitations, I opted to use LASSO and Elastic Net regularization methods, which offer a more efficient and consistent alternative. These techniques perform lag selection as part of the estimation process, avoiding the need for repeated model comparisons and hypothesis testing. This makes them particularly suited for rolling estimation frameworks, especially in this context given that each window is limited to 200 observations. Although these methods are commonly applied in high-dimensional settings (Gabauer et al., 2020; Demirer et al., 2018), they are also advantageous in smaller models that required frequent re-estimation, as they ensure computational tractability and reduce the risk of overfitting.

Additionally, I have also considered performing sequential hypothesis testing using t-tests on lagged coefficients. The reason why I did not apply them is because LASSO is more straightforward, less consuming, and represents a more automated alternative for selecting relevant lags without sacrificing interpretability than a t-test approach.

4.1 Least Absolute Shrinkage and Selection Operator

Before delving into the key findings of this regularization, it is fundamental to introduce some key concepts to better understand its purpose and relevance in the selection of the lag order of the VAR model. Starting by giving a brief context of the LASSO, it was first introduced by Tibshirani (1996) and designed to perform both parameter shrinkage and automatic variable selection in high-dimensional regression models. LASSO addresses the issues described above by adding an ℓ_1-norm penalty to the loss function. Considering the VAR context, from the equation (4), the penalized loss function of LASSO is given by:

$$\hat{\beta}_{\text{Lasso}} = \arg\min_{\beta} \left\{ \frac{1}{T} \sum_{t=1}^{T} \left\| \mathbf{y}_t - \sum_{i=1}^{p} \Phi_i \mathbf{y}_{t-i} \right\|_2^2 + \lambda \|\beta\|_1 \right\}, \tag{5}$$

where $\mathbf{y}_t$ and Φ_i denote the same designations as in (4), β is the stacked vector of all VAR coefficients, λ is the regularization parameter that controls the degree of penalization, $\|\beta\|_1 = \sum |\beta_j|$ denotes the ℓ_1-norm.

4.2 Elastic Net

Building upon the theoretical foundation of LASSO, Elastic Net combines both the ℓ_1-penalty of LASSO and the ℓ_2-penalty of Ridge regression. This model was developed by Zou and Hastie (2005) and allows for automatic selection of the relevant lag structure by shrinking less informative coefficients toward zero, while also stabilizing estimates in the presence of multicollinearity. Its objective function is defined as:

$$\hat{\beta}_{\text{ENet}} = \arg\min_{\beta} \left\{ \frac{1}{T} \sum_{t=1}^{T} \left\| \mathbf{y}_t - \sum_{j=1}^{p} \Phi_i \mathbf{y}_{t-i} \right\|_2^2 + \lambda \left(\alpha \|\beta\|_1 + \frac{1-\alpha}{2} \|\beta\|_2^2 \right) \right\}, \tag{6}$$

where $\|\beta\|_2^2 = \sum \beta_i^2$ is the squared ℓ_2-norm penalty (Ridge), $\alpha \in [0,1]$ determines the balance between the LASSO (ℓ_1) and Ridge (ℓ_2) penalties: when $\alpha = 1$, Elastic Net reduces to LASSO; when $\alpha = 0$, it becomes Ridge regression.

In the empirical implementation of both models, the regularization parameter λ was selected using the `cv.BigVAR()` function from the `BigVAR` package in R Studio. Unlike conventional cross-validation procedures designed for independently and identically distributed (i.i.d.) data, this method applies a time-series-specific approach based on rolling-window forecasts. By preserving the temporal ordering of the data, the function evaluates predictive performance sequentially and selects the value of λ that minimizes the out-of-sample mean squared forecast error (OOSMSFE). This ensures that the regularization is tuned in a way that reflects the structure of the data and captures the dynamic nature of the series.

As a conclusion, the primary objective of using regularization techniques was not properly estimate a full VAR model, but to efficiently and robustly identify which lagged relationships are most relevant for explaining the interactions between the volatilities of the three MSCI Extended ESG Focus Indices.

4.3 Variance Decompositions and Market Indices Connectedness

Relying on the findings of LASSO and Elastic Net, both models assume an optimal lag order of five, indicating that dynamic inter dependencies in the volatility time series extend across five trading days. The maximum lag order was initially set to ten to allow enough flexibility in capturing potential short-term dependencies, while avoiding overfitting.

Additionally, Augmented Dickey-Fuller (ADF) unit root tests were also conducted on each of the volatility series comprising $\mathbf{y}_t$, where the null hypothesis of a unit root was rejected in all cases at conventional significance levels. These results confirm that the series are stationary, supporting the use of a VAR in levels. I therefore opted by using a VAR with lag length of five, resulting in a 3-dimensional VAR(5), which is formulated as follows:

$$\mathbf{y}_t = \sum_{i=1}^{5} \Phi_i \mathbf{y}_{t-i} + \varepsilon_t \tag{7}$$

where Φ_i are 3×3 coefficient matrices and $\varepsilon_t \sim \mathcal{N}(0, V)$ is a vector of innovations with full residual variance-covariance matrix V. The innovations ε_t are assumed to be independently and identically distributed (i.i.d.) from an unspecified distribution with constant mean and variance, but not necessarily normally distributed. Following the Diebold and Yilmaz (2012), I transform the VAR into its infinite-order Moving Average (MA) representation: $\mathbf{y}_t = \sum_{i=0}^{\infty} A_i \, \varepsilon_{t-i}$, where A_i is a (3 $\times$ 3) matrices of coefficients that capture the dynamic response to past shocks. These matrices A_i obey the recursion $A_i = \Phi_1 A_{i-1} + \Phi_2 A_{i-2} + \cdots + \Phi_5 A_{i-5}$, with A_0 an 3×3 identity matrix and $A_i = 0$ for $i < 0$. This form enables the computation of Generalized Forecast Error Variance Decomposition (GFEVD), which is given by the following expression:

$$d_{ij}^{(H)} = \frac{\sigma_{jj}^{-1} \sum_{h=0}^{H-1} \left(e_i' \Psi_h V e_j\right)^2}{\sum_{h=0}^{H-1} \left(e_i' \Psi_h V \Psi_h' e_i\right)} \tag{8}$$

where σ_{jj} is the j^{th} diagonal element of the residual variance-covariance matrix

V i.e., the variance of the j^{th} shock; e_i and e_j are $n \times 1$ selection vectors with 1 in the i^{th} or j^{th} position, respectively; Ψ_h is the MA coefficient matrix at lag h, derived from the infinite-order MA representation of the VAR; V denotes the residual variance-covariance matrix estimated from the VAR model introduced in (7). The numerator captures the impact of shocks to variable j on the forecast error variance of variable i, while the denominator reflects the total forecast error variance of variable i at horizon H. The resulting value, $d_{ij}^{(H)}$, represents the share of forecast error variance in variable i that can be attributed to shocks in variable j.

To ensure the results are understandable and to support uniform aggregation across the rows, Diebold and Yilmaz (2012) suggest standardizing each row of the GFEVD matrix. This standardization guarantees that the portions for each variable i sum to unity across all j, resulting in:

$$\tilde{d}_{ij}^{(H)} = \frac{d_{ij}^{(H)}}{\sum_{j=1}^{3} d_{ij}^{(H)}} \tag{9}$$

The normalized decomposition $\tilde{d}_{ij}^{(H)}$ allows for the construction of the connectedness table represented in Table IV, which serves as the core representation of spillovers in the system. This approach allows for the calculation of total dynamic volatility spillover, directional spillovers and net spillovers.

Table IV: Connectedness Table / Network Adjacency Matrix, D

	x_1	x_2	$\cdots$	x_N	From Others to i
x_1	$\tilde{d}_{11}^H$	$\tilde{d}_{12}^H$	$\cdots$	$\tilde{d}_{1N}^H$	$\sum_{j=2}^{N} \tilde{d}_{1j}^H$
x_2	$\tilde{d}_{21}^H$	$\tilde{d}_{22}^H$	$\cdots$	$\tilde{d}_{2N}^H$	$\sum_{j=1, j\neq 2}^{N} \tilde{d}_{2j}^H$
$\vdots$	$\vdots$	$\vdots$	$\ddots$	$\vdots$	$\vdots$
x_N	$\tilde{d}_{N1}^H$	$\tilde{d}_{N2}^H$	$\cdots$	$\tilde{d}_{NN}^H$	$\sum_{j=1}^{N-1} \tilde{d}_{Nj}^H$
To Others From j	$\sum_{i=2}^{N} \tilde{d}_{i1}^H$	$\sum_{i=1, i\neq 2}^{N} \tilde{d}_{i2}^H$	$\cdots$	$\sum_{i=1}^{N-1} \tilde{d}_{iN}^H$	$\sum_{i=1, i\neq j}^{N} \tilde{d}_{ij}^H$

Each entry $\tilde{d}_{ij}^{(H)}$ measures the spillover from index j to index i at horizon H, expressed as a percentage of the total forecast variance for variable i. In other words, it gives the answer to a key question: "how much of index i's future uncertainty (at horizon H) is due to shocks arising with index j?".

4.4 Total Dynamic Volatility Spillover

Building on the variance decomposition framework, the next step focuses on the computation of the total dynamic volatility connectedness, which measures the overall degree of spillovers in the system. It quantifies the average portion of forecast error variance in each variable that is attributable to shocks from the other variables.

$$C(H) = \frac{\sum_{i \neq j} \tilde{d}_{ij}^{(H)}}{3} \times 100 \tag{10}$$

In order to capture the evolution of systemic volatility spillovers over time, the total dynamic volatility spillover is computed dynamically using a rolling window approach of 200 days (Kakran et al., 2023). This process yields a time series of $C(H)$ values, denoted $C_t(H)$, which reflects the degree of volatility spillovers at each point in time:

$$C_t(H) = \frac{\sum_{i \neq j} \tilde{d}_{ij,t}^{(H)}}{3} \times 100 \tag{11}$$

4.5 Directional Volatility Connectedness, "FROM" and "TO"

The measures of directional connectedness offer an understanding of where volatility shocks come from and where they go within the system. More precisely, the "*to*" others "*from*" i measure quantifies how much index i contributes to the volatility of all other indices, reflecting its role as a driver of systemic risk. The total directional connectedness "*from*" index i "*to*" all other indices j is $C_i^{\rightarrow}(H) = \sum_{j \neq i} \tilde{d}_{ji}^{(H)}$, given in (9).

Conversely, the "*from*" others "*to*" i metric indicates how much of the forecast error variance of index i is due to changes in all the other indices. Similarly, the total directional connectedness "*to*" index i "*from*" all other indices j is $C_i^{\leftarrow}(H) = \sum_{j \neq i} \tilde{d}_{ij}^{(H)}$, given in (9).

4.6 Net Directional and Pairwise Connectedness

To further examine bilateral relationships, the framework also includes the net pairwise connectedness measure, which isolates the relative contribution of one index to another. This metric compares the spillover "*from*" index j "*to*" index

i against the spillover in the reverse direction. The net total connectedness for index i is given by $C_i^{\text{net}}(H) = C_i^{\rightarrow}(H)$ - $C_i^{\leftarrow}(H)$.

Similarly, the net pairwise connectedness between indices i and j is given by $C_{ij}^{\text{net}}(H) = \tilde{d}_{ji}^{(H)}$ - $\tilde{d}_{ij}^{(H)}$. These measures are particularly useful in the context of this study, as they allow us to determine not only which ESG indices are more systemically important in terms of volatility transmission, but also to identify asymmetric dependencies between specific regional markets.

5 Results

This chapter presents the empirical findings derived from Diebold and Yilmaz (2012) connectedness framework applied to the selected MSCI Extended ESG Focus indices. It begins with the static connectedness Table IV, which summarizes the average directional spillovers among the three indices and proceeds to examine the evolution of system-wide connectedness using a rolling-window approach, followed by the analysis of directional and net spillover measures.

The empirical implementation of this study was carried out on R programming language (R Version 4.5.0), using the user-friendly and computationally efficient `spillover` package developed by Urbina (2024). The model specifications and connectedness measures presented in chapter 4 were produced using the `spilloverDY12()` function, which computes total, directional, and net volatility spillovers based on a 3-dimensional VAR(5) model.

5.1 Variance Decompositions and Market Indices Connectedness

Table V displays the static connectedness matrix, which summarizes the average pairwise volatility spillovers among the three MSCI ESG indices based on generalized forecast error variance decompositions described in section 4. The last two rows of the table report the total contribution of each variable to the system, including both own and cross-market effects.

The diagonal entries show that the majority of the volatility in each index is explained by its own shocks, particularly evident in the case of MSCI USA and Emerging Markets indices. Nonetheless, the remaining volatility, approximately 30 to 37% in each index, is driven by spillovers from others, which is considered economically significant.

Table V: Connectedness Table / Network Adjacency Matrix, D

	Vol_{USA}	Vol_{EFAFE}	Vol_{EM}	FROM Others
Vol_{USA}	70.50	19.73	9.77	29.50
Vol_{EAFE}	19.46	62.70	17.84	37.30
Vol_{EM}	13.29	17.18	69.53	30.47
TO Others	32.74	36.91	27.61	32.42
TO Others (including own)	103.24	99.62	97.14	300.00

The off-diagonal elements reveal a particularly strong bidirectional relationship between EAFE and USA volatilities. The spillovers from the USA to EAFE and from EAFE to the USA, respectively 19.73% and 19.46%, are the highest off-diagonal elements in the matrix, indicating a mutually influential dynamic between these two developed market regions. Additionally, the connection between EAFE and Emerging Markets seems to be particularly meaningful as well. The spillovers from EAFE to EM and vice versa, respectively, 17.84% and 17.18% represent the second strongest bilateral linkage, underlining EAFE's role as a key intermediary, transmitting volatility between developed and emerging markets.

As previously observed, EAFE stands out as both the largest transmitter and the largest receiver of volatility, contributing 36.91% to the forecast error variance of spillovers and 37.30% of its own variance being explained by external shocks. This balanced position highlights EAFE's central role in the volatility network, acting as both a source and a destination for systemic movements.

5.2 Total Dynamic Volatility Connectedness

Figure 3 displays the total dynamic volatility spillover, which measures the overall degree of spillovers in the system. This chapter aims not only to identify the intensity of interconnectedness among these indices, but also to understand how global ESG-related events, policy developments and investor sentiment shaped these dynamics over time.

During 2018 and early 2019, there has been a significant change in the investment landscape, where ESG factors have moved from being minor issues to central components of investment decision making, marking the initial alignment of ESG investment considerations across regions. Particularly, MSCI started to recognize key ESG trends such as the escalating impact of climate change and the

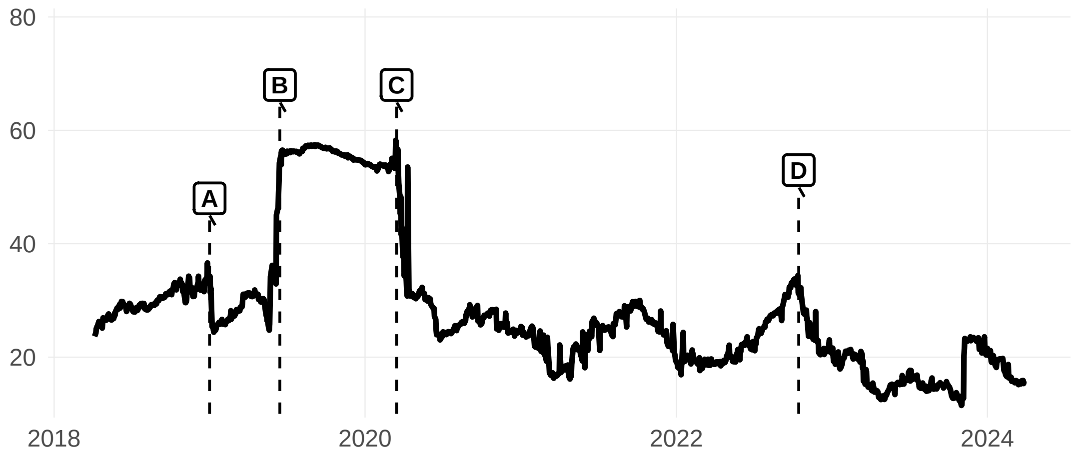

Figure 3: Total Dynamic Volatility Spillovers.
Notes: The letters indicate major events in volatility spillovers.
A - Global Convergence of ESG Narratives (Early 2019); B - MSCI ESG Ratings Updates (Mid-2019); C - COVID-19 crisis as a Systemic ESG Event (March 2020); D - Macro-Financial Shocks and Geopolitical Instability (Early 2023).

critical role of corporate leadership in fostering transparency and responsibility, by encouraging investors to actively engage with companies on these issues. As a result, total volatility spillovers began to build gradually showing an upward trend between 20% and 40% in 2018 and early 2019.

In mid-2019, MSCI implemented several ESG methodology updates (MSCI Inc. (2019)), including changes to its materiality map and the expansion of exclusion criteria, based on MSCI ESG Ratings. These modifications indirectly impacted the composition and risk profiles of the Extended ESG Focus Indexes. The resulting index adjustments and investor responses likely led to aligned shifts in asset holdings across regions, explaining the observed dramatic rise to around 55% in total volatility spillovers at that time.

The outbreak of COVID-19 in early 2020 registered a turning point, acting as both a global financial crisis and an ESG shock. The pandemic exposed weaknesses across all ESG dimensions: from insufficient worker safeguards and vulnerable supply chains to ineffective crises response and renewed focus on ecological sustainability. As a consequence, ESG-focused investment approaches faced rigorous evaluation, which led to a significant rise in volatility spillovers, achieving its highest value of almost 60% and reflecting the realignment of investor behavior across regions in response to common sustainability shocks.

Following this dramatic spike, the connectedness measure drops sharply and enters a more moderate phase, fluctuating around lower levels between 15% and

30% through 2021 and early 2022. As markets adapted to the post-pandemic environment, ESG-aligned portfolios benefited from reduced exposure to sectors most vulnerable to persistent macroeconomic uncertainty, contributing to more divergent responses across indices, and, consequently, lower levels of overall volatility spillovers.

Although it was expected to observe a significant increase in late February 2022 caused by the Russia-Ukraine war as registered in the time-series plot in section 3.4, the same does not prevail in the case of total dynamic volatility connectedness. This occurrence results from a combination of regional and behavioral market factors. Specifically, the fact that MSCI Extended ESG Focus Indices were not uniformly affected by the war results in a partially transmission of volatility during that period and, consequently, in an overall upward trend with small fluctuations between 15% and 35%, and no discernible structural break.

The moderate rise in total volatility spillovers observed in 2023 may reflect a combination of overlapping global risks that affected all three regions, such as persistent inflation, tightening monetary policy cycles in both developed and emerging economies, and the escalation of geopolitical tensions (e.g., the Israel–Hamas conflict and ongoing Russia–Ukraine war).

Overall, the changes in volatility spillovers within the MSCI Extended ESG Focus Indices indicate more than just correlations between financial markets - it captures the shifting landscape of sustainable finance itself. During times of regulatory alignment or global events, the MSCI Extended ESG Focus Indices operated harmoniously, resulting in high levels of interconnectedness. Conversely, as regional narratives, policies, and investor priorities began to diverge, the transmission of volatility became more moderate and idiosyncratic.

5.3 Directional Volatility Connectedness, "FROM" and "TO"

Figure 4 shows the directional volatility spillovers. This measure allows to assess which indices are most affected by external shocks but also which ones are most responsible for spreading instability to others.

Across the observed time frame, all three indices exhibit varying levels of susceptibility, especially during key global and regional events. The year 2020 marks the most dramatic episode, where this global shock caused by the COVID-19 onset triggered elevated systemic risk, resulting in a sudden rise in directional volatility spillovers, reaching the 20% almost for all cases. This occurrence confirms the

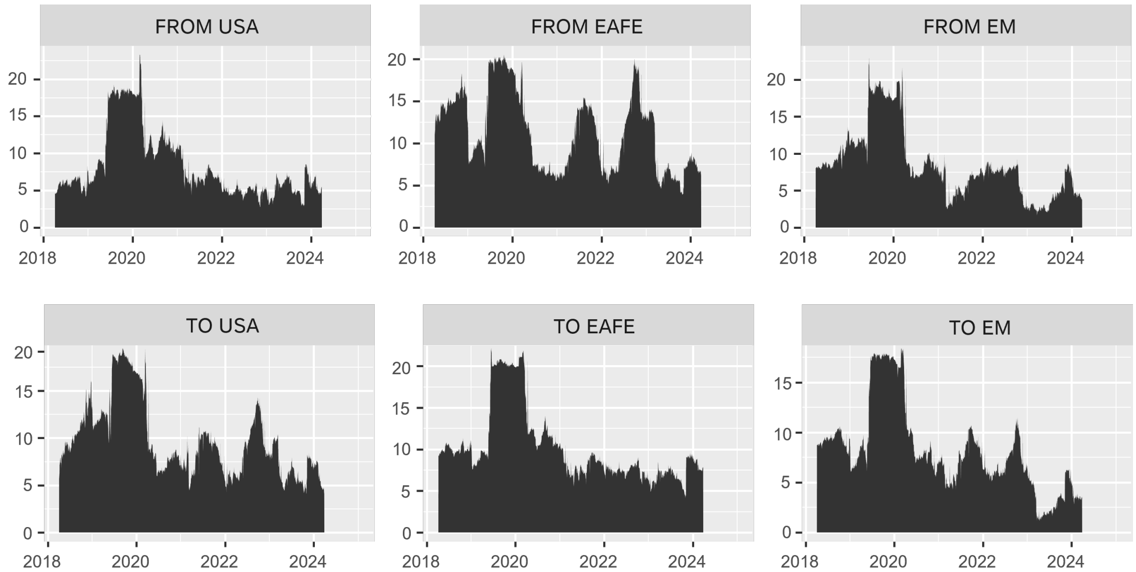

Figure 4: Directional Volatility Connectedness.

nature of the shock: volatility spillovers were not limited to a particular market, but flowed in multiple directions, intensifying a cycle of risk escalation worldwide.

Following this initial shock, the system behavior starts to diverge: transmitted volatility declines more sharply than received volatility for the USA and EM indices, achieving a magnitude between 5% and 15%. Conversely, EAFE index stands out as the main transmitter of volatility, particularly in 2022 and early 2023, reaching values closer to 20%, due to the region-specific shocks. The energy supply disruptions, inflationary pressures, and heightened geopolitical uncertainty caused by the Russia-Ukraine war led to sharp market adjustments within the EAFE region, which were transmitted to other markets through trade and investor sentiment channels.

Overall, the directional spillovers plots illustrate a slow transformation in the roles played by the indices. The early stage of shared influence during the COVID-19 crisis gives way to a more asymmetric structure, where roles become more defined. EAFE increasingly emerges as a key transmitter of volatility, consistently exhibiting high *from* connectedness. Contrarily, the USA index transitions into a persistent receiver, with sustained *to* connectedness and declining transmission over time, especially after 2020. Moreover, after briefly participating in both transmitting and receiving during the initial crisis phase, the EM index, gradually shifts to the edges of the network, showing a reduced influence in both directions.

This evolving configuration underlines the need to monitor not only the magnitude but also the directional flow of volatility, especially within ESG frameworks where regional and sectoral sensitivities may diverge from those of traditional benchmarks.

5.4 Net Directional and Pairwise Connectedness

Figures 5 and 6 display the net directional volatility spillovers and the net pairwise volatility spillovers, respectively. These measures reinforce the directional spillovers from last section, identifying clearly net transmitter and receiver roles and the most evident bilateral spillovers.

What is particular interesting is that net transmitter and receiver roles are not static, but event-dependent. For instance, EAFE consistently acts as a net transmitter of volatility, particularly in 2022 and early 2023, reflecting the region's exposure to localized yet globally contagious shocks caused potentially by the Russia–Ukraine war and energy market dislocations.

In contrast, USA consistently shows negative net spillovers, excepting in 2020. Despite its size and importance, its MSCI Extended ESG Focus Index version functions largely as a shock absorber. This suggests a more defensive or diversified structure, or possibly stronger monetary and fiscal buffers that reduce its role as a global transmitter in this particular ESG sample. Regarding the EM index, the net spillover oscillates asymmetrically between a range of positive and negative values of around -5% and 5%, confirming its role as a reactive node in the network: occasionally noisy during financial stress, but not persistently influential.

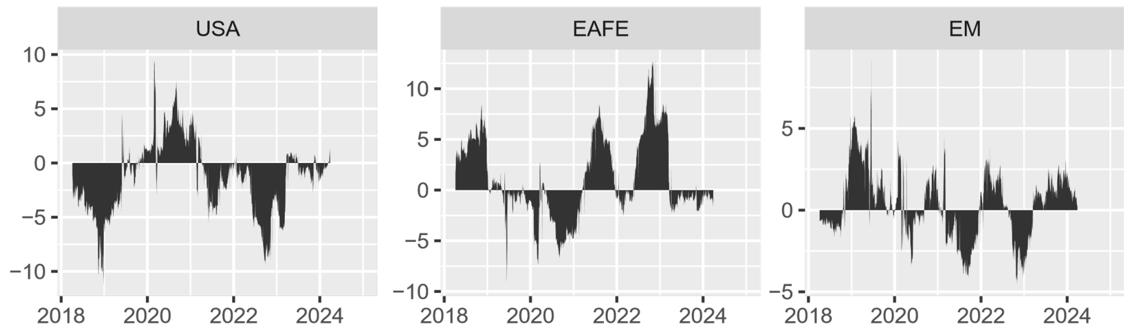

Figure 5: Net Directional Volatility Connectedness.

Concerning the net pairwise connectedness analysis, the USA-EAFE stands out as the most persistent asymmetric pair, with EAFE consistently acting as a net transmitter of volatility across nearly the entire period. Similarly, in the EAFE-EM bilateral relationship, EAFE index remains a stable transmitter, confirming its central role in propagating systemic risk.

On the other hand, the USA-EM relationship is more balanced, with directionality movement over time. During COVID-19 crisis, the USA becomes a net transmitter to EM, shifting to a predominantly received role in the subsequent period. Overall, the bilateral dynamics confirm the EAFE role as the primary origin of volatility spillovers, while the USA and EM act as volatility receivers, with EM particularly positioned at the periphery of the network.

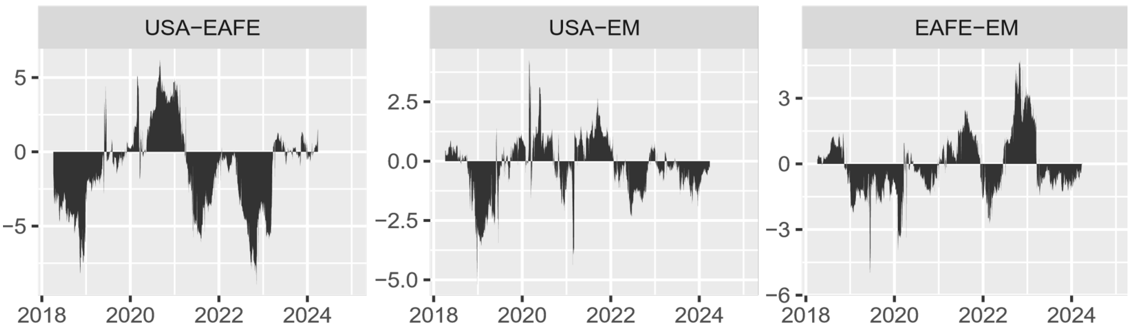

Figure 6: Net Pairwise Volatility Connectedness.

6 Conclusions

This study was set out to explore volatility spillovers among regional ESG equities. The analysis covered daily data from 2016 to 2024 and employed the Diebold and Yilmaz (2012) connectedness framework to quantify total, directional, and net spillovers, both statically and over time. Ultimately, I identified how volatility shocks in one regional ESG market influence others, and whether developed and emerging markets differ systematically in their exposure and contribution to volatility transmission.

The results confirm that developed markets, particularly, the EAFE region, tend to act as dominant transmitters of volatility, while Emerging Markets play a more passive and idiosyncratic role. These findings are consistent with differences in ESG regulatory frameworks, reporting standards, and institutional investor behavior, which are typically more advanced and coordinated in developed economies, as supported by studies such as Karkowska and Urjasz (2025).

A particularly important insight is the evolving role of the United States index. While traditional financial literature (Kakran et al., 2023) commonly identifies the U.S. as a primary transmitter of volatility in global equity markets, reflecting its size, liquidity, and centrality in conventional financial systems, this thesis shows different results in the ESG context. Initially exhibiting moderate two-way spillovers, it transitions over time into a consistent net receiver of volatility, as confirmed by Shaik and Rehman (2023). This behavior likely stems from the structural composition of the MSCI USA ESG Focus Index, which excludes high-risk sectors and emphasizes large-cap, high-governance firms - characteristics that may reduce its vulnerability to external contagion.

The time-varying analysis provides further nuance, showing that spillover intensity is not static but highly responsive to global events, such as COVID-19 crisis, where the total volatility connectedness spiked to nearly 60%, reflecting widespread uncertainty across ESG domains - public health, labor standards, and corporate governance.

Despite its valuable insights, this study is subject to several limitations that open opportunities for future research. Firstly, the analysis is restricted to three regional ESG indices. While this deliberate choice ensured methodological clarity and comparability, since all indices are constructed using the same ESG screening methodology, it also limits the generalization of the findings. Including additional regions, such as Latin America or Eastern Europe, or exploring sub-regional markets, could reveal more nuanced dynamics, especially in ESG ecosystems with distinct political, regulatory, or developmental characteristics.

Secondly, the study relies on a linear, rolling-window VAR model to estimate spillovers. While this approach is widely accepted in the connectedness literature, it assumes parameter stability within each window and may fail to capture nonlinearities or abrupt regime changes during periods of financial stress. Future work could implement more flexible frameworks, such as time-varying parameter VARs (TVP-VARs), Markov-switching models, or machine learning-based techniques, which can adapt to structural shifts and better capture the dynamic nature of ESG-related spillovers.

Thirdly, while the Diebold and Yilmaz (2012) connectedness framework captures the statistical strength of volatility transmission, it does not distinguish between different types of shocks, whether they arise from fundamentals, regulatory announcements, geopolitical events, or investor sentiment. Given the increasing importance of behavioral and reputational factors in ESG investing, future research could integrate text-based sentiment analysis, ESG news flow, or controversy indices to differentiate the sources and channels of volatility, as highlighted by Anghel and Caraiani (2025).

Beyond its academic contributions, this study also offers practical insights for financial institutions that desire to enhance the development and calibration of financial pricing models. The identification of time-varying, directional volatility spillovers across regional ESG indices can inform more accurate modeling of correlation structures, shock transmission paths, and volatility regimes, all of which are critical components in pricing ESG-linked financial instruments. For example, recognizing that the US index consistently behaves as a net receiver of volatility implies that models should treat external shocks, particularly those originating in EAFE or EM regions, as primary drivers of valuation adjustments in US-based ESG assets. These findings can be directly incorporated into scenario design, risk premia estimation, and stress testing routines, particularly for instruments sensitive to global ESG risk factors, such as green bonds, ESG ETFs, or climate-indexed derivatives.

Ultimately, as the financial industry continues to integrate sustainability criteria into risk and valuation models, a nuanced understanding of regional ESG spillovers will become increasingly vital for asset managers, policymakers, and financial institutions alike.

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A Appendices

A.1 Morgan Stanley Capital International USA Extended ESG Focus Index - Composition

Sector Weights		**Top 10 Constituents**			
Sector	**Weight (%)**	**Company**	**Index Wt. (%)**	**Parent Index Wt. (%)**	**Sector**
Information Technology	32.43	NVIDIA	6.50	6.39	Info Tech
Financials	13.93	Microsoft Corp	6.36	6.27	Info Tech
Health Care	10.25	Apple	5.71	5.83	Info Tech
Consumer Discretionary	9.96	Amazon.com	3.69	3.74	Cons Discr
Industrials	9.49	Alphabet C	2.95	1.66	Comm Srvcs
Communication Services	8.46	Meta Platforms A	2.55	2.72	Comm Srvcs
Consumer Staples	5.54	Broadcom	2.08	2.08	Info Tech
Energy	3.31	Tesla	1.91	1.93	Cons Discr
Real Estate	2.28	JPMorgan Chase & Co	1.35	1.43	Financials
Materials	2.26	Visa A	1.32	1.22	Financials
Utilities	2.08				
Total	**100.00**	**Total**	**34.42**	**33.28**	

A.2 Morgan Stanley Capital International EAFE Extended ESG Focus Index - Composition

Sector Weights		**Country Weights**		**Top 10 Constituents**			
Sector	**Weight (%)**	**Country**	**Weight (%)**	**Company**	**Index Wt. (%)**	**Parent Index Wt. (%)**	**Sector / Country**
Financials	24.54	Japan	21.73	SAP	1.93	1.72	Info Tech / DE
Industrials	18.11	United Kingdom	14.72	ASML HLDG	1.72	1.59	Info Tech / NL
Health Care	10.77	France	10.64	NESTLE	1.34	1.52	Cons Staples / CH
Consumer Discretionary	10.13	Switzerland	9.88	NOVARTIS	1.32	1.23	Health Care / CH
Information Technology	9.14	Germany	9.86	NOVO NORDISK B	1.26	1.21	Health Care / DK
Consumer Staples	8.60	Others	33.17	ASTRAZENECA	1.21	1.22	Health Care / GB
Materials	5.39			HSBC HOLDINGS (GB)	1.10	1.15	Financials / GB
Communication Services	4.55			COMMONWEALTH BANK OF AUS	1.07	1.03	Financials / AU
Energy	3.43			SONY GROUP CORP	1.07	0.88	Cons Discr / JP
Utilities	3.40			SCHNEIDER ELECTRIC	1.04	0.75	Industrials / FR
Real Estate	1.95			**Total**	**13.06**	**12.30**	
Total	**100.00**	**Total**	**100.00**				

A.3 Morgan Stanley Capital International Emerging Markets Extended ESG Focus Index - Composition

Sector Weights		**Country Weights**		**Top 10 Constituents**			
Sector	**Weight (%)**	**Country**	**Weight (%)**	**Company**	**Index Wt. (%)**	**Parent Index Wt. (%)**	**Sector / Country**
Financials	29.72	China	28.83	TAIWAN SEMICONDUCTOR MFG	10.18	9.63	Info Tech / TW
Information Technology	23.23	Taiwan	20.06	TENCENT HOLDINGS LI (CN)	4.58	4.97	Comm Srvcs / CN
Consumer Discretionary	13.9	India	17.87	SAMSUNG ELECTRONICS CO	2.56	2.36	Info Tech / KR
Communication Services	10.68	South Korea	9.87	ALIBABA GRP HLDG (HK)	2.50	2.85	Cons Discr / CN
Industrials	5.15	South Africa	4.18	HDFC BANK	1.83	1.56	Financials / IN
Consumer Staples	4.29	Others	19.18	RELIANCE INDUSTRIES	1.59	1.23	Energy / IN
Materials	4.01			CHINA CONSTRUCTION BK H	1.55	1.05	Financials / CN
Energy	3.16			FIRST FINANCIAL HLDG CO	1.29	0.12	Financials / TW
Health Care	2.9			E.SUN FINANCIAL HOLDINGS	1.25	0.17	Financials / TW
Utilities	1.91			ICICI BANK	1.15	1.08	Financials / IN
Real Estate	1.07			**Total**	**28.47**	**25.01**	
Total	**100.00**	**Total**	**100.00**				