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# Dynamic linkage between environmental segments of stock markets: the role of global risk factors

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**ABSTRACT**

This study evaluates the links between representative indices of companies with high environmental performance and the propensity of such indices to economic and financial shocks. Five indices, representing environmental segments and four global macroeconomic and financial variables, were analyzed over a thirteen-year period, which included various crisis moments, such as the sovereign debt crisis, the COVID-19 pandemic and the onset of the Russia/Ukraine conflict. Using dynamic and nonlinear models, our research reveals statistically significant and consistent relationships between the variables under investigation, particularly during periods of global financial and pandemic crises. The analysis revealed that the VIXCLS is the most influential global risk factor, with certain risk factors being influenced by environmental segments, particularly Alternative Energy. This influence can create conditions conducive to contagion risk and diminish the benefits of portfolio diversification. This study contributes to a deeper understanding of the connection between environmental investments and their vulnerability to significant global events and risks.

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Connectivity; crisis periods; DCC-GARCH; environmental investment; portfolio diversification; transfer entropy

## 1. Introduction

Understanding the role of companies and investment in society has evolved greatly over time. According to Friedman (1970), companies' central objective is restricted to maximizing shareholder value, with the social dimension representing an additional cost and a penalty on their profits. In opposition to this perspective, the stakeholder theory, which finds its main defender in Freeman (2008), considers that companies have responsibilities towards their shareholders and other stakeholders to satisfy the interests of all of them.

Several factors, such as environmental damage, global warming, water scarcity, human rights, poverty, crisis, and financial scandals, associated with bad governance practices, have led to a greater appreciation of sustainability by stakeholders. In recent years,

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institutional and private investors have been attracted to move to financial investments toward green and environmentally sustainable projects (Agliardi and Agliardi 2021).

Investors are willing to consider environmental, social and governance issues in their investment decisions, meeting traditional financial objectives without neglecting society's sustainability, being documented, for example by Ghosh et al. (2022) that green and sustainable finance offers benefits and opportunities for stock exchanges, especially for energy stocks. As a result, many businesses are focusing on sustainability and adopting an eco-friendly business model, which helps the environment, helps sustainability, and attracts investors (Ghosh et al. 2022).

Awareness of the sustainability issue has been the main reason for the emergence of sustainable stock indices, which progressively attract investors' attention (Cortez et al. 2009). To adapt to the changes that have taken place in management models in general, financial markets have operated an evolutionary process, in order to present new investment alternatives, namely those linked to socially responsible investment. The increasing relevance of sustainable investment in the global context is reflected in the fact that the value of global assets in this type of investment has grown significantly in recent years, from 13.3 trillion dollars in 2012 to 30.7 trillion dollars in 2018 (GSIA 2019). Cryptocurrencies have emerged as a new asset class and gained popularity in recent years, similar to socially responsible investments. However the energy consumption associated with cryptocurrency mining and blockchain consensus mechanism has raised concerns about their environmental impact. As ecological concerns grow, the media focuses more on alternative energy sources. Umar, Abrar, et al. (2022) analyzed how the attention given to cryptocurrency's environmental effects affects both dirty and clean energy assets. Their findings have shown that dirty bonds and equities contribute more to return and volatility spillover, while the impact of this environmental attention is stronger on dirty and green equities than on dirty and green bonds in the financial market.

These sometimes contradictory results are the basis for this research project, which aims to evaluate the relationship between five indices of the environmental segments between 20th January 2009 and 28th March 2022 (to include different crisis moments). Furthermore, the globalization and integration of financial markets may contribute to the possible transmission of information not only between the environmental stock indices but also between them and several macroeconomic and financial variables. Thus, in addition to the five indices of environmental segments, two indices (representing uncertainty in the stock markets and reflecting contingent fluctuations in the global financial system), a macroeconomic variable and a stock index were selected. They were selected to identify possible channels of contagion between the segments studied. Furthermore, identifying whether specific global risk factors could act as transmitting channels for spillovers between environmental stock indices in the same way they act for traditional ones and how this mechanism has evolved over time is also important and constitutes another motivation for this study.

Despite some investigation into the transmission of risk and possible contagion between sustainable and traditional investment, and concerning the performance of both investment segments (see, for example, Kenourgios, Naifar, and Dimitriou 2016; Hkiri et al. 2017; Gabriel and Pazos 2017, 2018; Shahzad et al. 2017; Umar, Kenourgios, Naem, et al., 2020), the study of connectivity between representative indices of environmental investment needs further and deeper investigation. Although some work has been done on the connectivity between sustainable investment segments, a research gap remains. There are no known studies that evaluate and quantify the information flow and simultaneously identify the dominant direction between environmental segments, advocating the sustainability objectives of the 2030 Agenda and identifying transmission channels of a macroeconomic and financial nature. Thus, this research aims to evaluate the relationship between environmental stock indices and macroeconomic/financial variables, considering sustainability objectives. Motivated by sustainable investment growth, the study also aims to explore the role of global risk factors in transmitting spillovers between environmental indices.

Methodologically, we start by estimating a dynamic conditional correlation model, and complement the analysis with a dynamic study of the relationships between indices through transfer entropy (TE). This study reveals that information transmission between different environmental stock market segments is not stable and varies over time. External events, such as financial crises and the COVID-19 pandemic, significantly impact this transmission process, increasing its intensity during crisis periods. Some environmental stock market segments, particularly Alternative Energy, contribute to the transmission of information, which can reduce portfolio diversification benefits. The VIXCLS, a global risk factor, significantly influences environmental segments and contributes to creating conditions that could facilitate contagion risk. This research highlights the importance of recognizing the dynamic nature of information transmission in environmental investments. Policymakers and investors must be attentive during crisis periods, as these segments are more vulnerable to external shocks. Identifying net contributors and influential risk factors can guide targeted interventions to manage contagion risk and enhance portfolio diversification. Therefore, policymakers should consider the evolving global landscape and the role of influential risk factors in sustainable investment strategies to mitigate risks associated with external shocks.

The remainder of this paper is organized as follows: after this introduction, Section 2 reviews the literature on sustainable investment. Section 3 presents the hypotheses formulated and develops them. Section 4 presents the data description and methodology. Section 5 presents the preliminary results. Section 6 presents the main empirical results and the respective discussion. Finally, Section 7 presents the main conclusions.

## 2. Literature review

The first work on the connection between different stock markets concluded that the behavior of market indices fundamentally depended on idiosyncratic factors, indicating that these indices offered opportunities for diversifying investment internationally (Grubel 1968; Ripley 1973; Bertoneche 1979). However, the economic and financial integration processes, as well as episodes of stock market crashes and high volatility (e.g. GFC), contributed to the progressive strengthening of the proximity between international stock markets, causing a decrease in investment diversification opportunities (Mandigma 2014; Gabriel and Manso 2014; Elsayed and Yarovaya 2019; Zhang and Broadstock 2018; Umar and Suleman 2017; Alexakis et al. 2021; Engle and Campos-Martins 2023; Kumar, Singh, and Rao 2023).

With the largest international stock market capitalization, with about 43% of the world capitalization of listed companies (World Bank 2020), the US stock market has been highlighted in several studies due to its role in other markets, with several authors concluding that the US acts as a driver of movements in other markets (e.g. Mandigma 2014; Gabriel and Manso 2014; Gabriel and Pazos 2018; among others). In turn, Tsai (2014), Akhtaruzzaman et al. (2021), and Kang and Lee (2019), using the spillover index of Diebold and Yilmaz (2012), attributed to the US market the ability to influence other markets, with a positive spillover effect. Umar, Kenourgios and Papathanasiou (2020) studied the connectedness of the most significant global equity indices that comprise companies with the highest environmental, social, and governance (ESG) performance and various influential macroeconomic and financial variables. They found statistically significant and consistent transmissions between the analyzed equity indices with dynamic patterns during some specific crisis periods. The VIX index was identified as the primary transmission mechanism for shocks among ESG markets. These findings highlight the risk of contagion and the diminishing portfolio diversification benefits during turbulent periods.

In an attempt to deepen the study of the behavior of the main international stock indices, several studies chose to use global risk factors in their respective methodological proposals, namely the index of uncertainty in economic policy, the implied volatility, and the price of oil, among others, to link the risk-taking of market participants to variables with a decisive influence on the global financial environment.

Regarding global risk factors, the US economic policy uncertainty index (EPU) is a crucial global risk factor that measures the level of uncertainty surrounding economic policies in various countries, it serves as a valuable tool for assessing the global risk factor associated with policy uncertainty. Constructed by Baker, Bloom, and Davis (2016), it has been considered in several recent studies as a relevant variable in stock market behavior. This index defines uncertainty in monetary, fiscal or regulatory policy matters, and is calculated based on newspaper articles, namely about economics, politics and uncertainty (Engle and Campos-Martins 2023).

Changes in the EPU index can negatively affect stock market profitability due to its direct relationship with economic growth, employment, foreign direct investment, and foreign trade (Christou et al. 2017; Guo, Zhu, and You 2018; Hu, Kutan, and Sun 2018; Phan, Sharma, and Tran 2018; Xiong, Bian, and Shen 2018; Wang, Li, and He 2020).

Several studies have considered implied volatility as predicting stock market behavior. The most popular and monitored implied volatility index is the VIX, developed by the Chicago Board Options Exchange (CBOE), which is considered a proxy for investor fear (Whaley 2000) and a good indicator of the level of risk in the US and global capital markets (Traub et al. 2000). Regarding volatility, the finance literature has long identified the stylized fact of asymmetric volatility, that is, asset profitability is negatively correlated with the respective volatility (Bae, Kim, and Nelson 2007).

Several studies have examined the relationship between the VIX and stock market returns. Giot (2005) concluded that US stock futures returns are always positive after high US stock market volatility levels. Guo and Whitelaw (2006) concluded that the VIX is mean-reversible, suggesting a strong negative and contemporary relationship between changes in the VIX and stock market returns. Simlai (2010) discovered that high levels of the VIX accompany falls in prices on the S&P 500 index. Sarwar (2012) identified a significant negative and asymmetric association between the returns of the VIX and the S&P 500. Rapach, Strauss, and Zhou (2013) concluded that the VIX has important cross-influences on the returns of stocks in non-industrialized countries.

Basher and Sadorsky (2016) underline that the VIX is useful in hedging stock market assets from emerging markets. In a complementary way, Shu and Chang (2019) found that the VIX exerts a dominant influence on equity markets returns and provides significant flow for these markets. Despite the growing weight of natural gas and renewable energies, oil remains the main primary energy source, accounting for 33.1% of global primary energy consumption in 2019 (BP 2020), being used in several studies as an explanatory factor of stock market asset prices. Several studies were carried out on the spillover effects between the two markets, using different models and reaching mixed conclusions (e.g. Mensi et al. (2013), Arouri, Jouini, and Nguyen (2012), Chang, McAleer, and Tansuchat (2013), among others). Recent studies highlight the importance of analyzing this relationship over time, as it changes in different periods (e.g. Broadstock and Filis (2014), Sadorsky (2014) and Antonakakis, Chatziantoniou, and Filis (2017)) concluding that the study of the relationship established between the two investment sectors should not be limited to static analysis. It should be made considering a time-varying analysis since the nature of this relationship changes at different moments in time. Other research has focused on the impact of oil price uncertainty on the stock markets, with studies showing that it affects returns and volatility in markets such as the Middle East and Africa, China and GCC (e.g. Dutta, Nikkinen, and Rothovius (2017), Xiao et al. (2018), Alqahtani, Klein, and Khalid (2019)). Furthermore, the association between oil market uncertainty and the Islamic stock market is found to be heterogeneous and asymmetric (Lin and Su 2020). Joo and Park (2021) provide evidence of the impact of oil price volatility on the stock returns of major oil-importing countries.

Sustainability is a key focus in society today, with various initiatives shaping public opinion and influencing decision-makers. One important initiative is the United Nations' 2030 Agenda, which introduced the 17 Sustainable Development Goals (SDGs). The financial system and investment are highlighted as essential components in achieving sustainability goals.

Sustainable investment has gained attention from investors and academics, but there is limited scientific research on the connectivity between different segments of sustainable investment. The existing research focuses on three main research areas. The first area compares the performance of a sustainable investment to traditional investment. Some notable studies in this area include the work of Martínez-Ferrero and Frías-Aceituno (2015), Climent and Soriano (2011), and Oikonomou, Platanakis, and Sutcliffe (2018). Another area of study evaluates the impact of the ESG dimensions on company value, with studies by Li et al. (2018) and Fatemi, Glaum, and Kaiser (2018) contributing to this field. The third area explores the connectivity and information transmission between sustainable indices. Standout studies in this area include those by Gabriel and Pazos (2017, 2018) and Reboredo and Ugolini (2020). The first two studies have found short-term similarities in the behavior of sustainable segments but have no identified long-term equilibrium relationships. The last study has shown that the green bond market receives spillover effects from traditional investment markets. While there are conflicting findings in several studies on ESG investment, investors increasingly assume that investing in sustainability will lead to long-term viability and attractive stock returns(Umar and Gubareva 2021). However the COVID-19 pandemic may potentially affect this assumption and limit the traditional recovery of companies in relation to ESG issues.

Globalization and digitization contribute to the almost instantaneous spread of news (Engle and Campos-Martins 2023). The interconnectedness of financial markets has led to widespread adverse effects. However, investors responded resiliently, increasing their investments in responsible investment during the crisis (Omura, Roca, and Nakai 2021). Omura, Roca, and Nakai (2021) investigated the performance of SRI and ESG investments against conventional investments during the COVID-19 pandemic, and the results confirmed the outperformance of the SRI indices during the pandemic. Umar and Gubareva (2021) and Umar et al. (2021) employed wavelet analyses to study the interdependence between some Ravenpack indices and the volatility of five ESG Leaders' indices. Both studies found predominantly medium to high coherence between various ESG indices vis-à-vis Ravenpack indices, indicating the diversification potential of the ESG indices in the COVID-19 pandemic. Differences were found in the coherence patterns across geographical indices, supporting the usage of ESG investments for diversification and downside hedge strategies. Akhtaruzzaman, Boubaker, and Umar (2022) supplemented the work of Umar and Gubareva (2021), including the European Market Union (EMU) ESG leader index, and found strong connectedness between ESG leader indices and the media coverage index (MCI) during the pick of the pandemic, highlighting the role media in spreading contagion. The study also allowed to identify the US as a net receiver across the network, leading the authors to conclude that the US was the most affected country during the pandemic.

## 3. Hypotheses development

The literature review explores the connectivity and information transmission between environmental stock market segments. Previous studies found that international stock markets have changed due to economic integration, financial integration, market crashes, and volatility. The US stock market has a significant influence on other markets, particularly during turbulent times, with the VIX acting as a key mechanism for transmitting shocks among ESG markets.

Global risk factors, such as the EPU and VIX indices, and oil prices, have been recognized for their impact on stock market asset prices. These factors contribute to the dynamics of stock market returns and volatility, influencing investor behavior and risk perception. The relevance of sustainability, as emphasized by the 2030 Agenda and Sustainable Development Goals (SDGs), has led to an increased focus on sustainable investment.

While previous research has explored various aspects of ESG investment, a gap exists in understanding the connectivity between different environmental investment segments. The literature suggests that sustainable investments, particularly ESG-driven companies, demonstrated resilience during the COVID-19 pandemic, with responsible investments outperforming conventional ones. The faster spread of news in the era of globalization and digitization contributes to the interconnectedness of financial markets, shaping investor behavior during crises.

No studies have evaluated and quantified the information flow between environmental segments and identified dominant directions and transmission channels of macroeconomic and financial nature. The transmission of information between environmental stock market segments is not stable and is likely influenced by global events like financial crises, pandemics, and geopolitical tensions. Thus, we formulate the first hypothesis:

H1. The transmission of information between environmental stock market segments don't remains stable over time, being affected by important events.

Considering the works of Umar, Kenourgios and Papathanasiou (2020), Reboredo and Ugolini (2020), Umar, Bossman, et al. (2022), and Engle and Campos-Martins (2023), among others, we anticipate observing fluctuations in the connectivity patterns between environmental stock market segments, with shifts during critical events, being expected that after applying the methods proposed, the results reveal different levels of information transmission over different time periods.

Crisis periods like the COVID-19 pandemic or the Russia-Ukraine war disrupt the flow of information between environmental stock market segments. Uncertainty, market reactions, and investor behavior during crises can change how information is shared between these segments. Considering the works of Gabriel and Pazos (2018), Umar, Kenourgios and Papathanasiou (2020), Umar et al. (2021) and Kumar, Singh, and Rao (2023), among others, we formulate our second hypothesis:

H2. Specific crisis periods interfere in the process of information transmission.

We expect to observe distinct patterns of information transmission during crisis periods, with potential spikes or alterations in connectivity. The methods applied should confirm that crisis periods have a significant impact on the transmission of information between segments.

Recognizing the interconnectedness of environmental stock market segments, it is plausible that certain segments exert more influence on the overall information transmission network, i.e. some segments may act as hubs, contributing more significantly to the transmission of information to other segments. This led us to formulate our last hypothesis:

H3. Some environmental stock market segments are net contributors.

Based on the works of Umar, Bossman, et al. (2022), Engle and Campos-Martins (2023), and Mirza et al. (2023), among others, we anticipate identifying specific segments that play a pivotal role in information transmission, acting as net contributors. Thus, it is expected that after applying the methods proposed, the results point to the existence of such influential segments, shedding light on the hierarchical structure of connectivity within environmental stock markets.

We firmly believe that our work holds significant importance and offers effective contributions for several compelling reasons. Firstly, we have conducted an in-depth study on the interconnectivity of various environmental investments over time. This aspect is of utmost significance as it enables us to comprehend the ripple effects that one investment can have on others. Moreover, we have analyzed data from distinct periods, including the financial crisis, the ongoing COVID-19 pandemic, and the war between Russia and Ukraine. Our objective was to assess the profound impact of these events on the interconnectedness of environmental investments. By doing so, we aimed to shed light on how these critical occurrences can influence the dynamics of environmental investments.

Furthermore, we have delved deep into the intricate relationship between global risks and the interconnection of different environmental investments over time. This facet holds high importance as it allows us to grasp how changes in the global landscape can significantly impact investments.

In essence, our work is a valuable tool for comprehending the intricate web of relationships within environmental investments and how significant events and global risks can profoundly influence them. Understanding these dynamics comprehensively enables us to confidently make informed decisions and navigate the ever-changing investment landscape.

## 4. Data and methodology

### *4.1. Data*

The data analyzed in this study were obtained from the Thomson Reuters DataStream, covering a period from 20th January 2009 to 28th March 2022. Several MSCI environmental stock indices (alternative energy, sustainable water, green construction, clean technology and pollution prevention) were selected as a proxy for environmental stock investment. In order to incorporate the global financial environment in the analysis, and identify possible channels that transmit spillovers between the environmental stock indices, several risk proxies were also selected, namely the VIX, EPU, and DJ indices, and Brent (as a factor of uncertainty in the economy, because oil price fluctuations, increase firms' and households' uncertainty about investment and consumption decisions (Bernanke 1983; Edelstein and Kilian 2009), as also a factor of uncertainty in the stock markets (Dutta, Nikkinen, and Rothovius 2017; Xiao et al. 2018; Alqahtani, Klein, and Khalid 2019; Lin and Su 2020; Joo and Park 2021). Furthermore, oil price shocks have a significant influence on inflation, which can, in turn, contribute to economic uncertainty. In the same way, the geopolitical tensions in oil-producing regions can lead to sudden price spikes, which can introduce uncertainty into economic forecasts). A brief description of them is presented in Appendix A, Table A.1.

Data frequencies matter both statistically and economically (Narayan and Sharma 2015), being found in the literature some discussion concerning data frequency selected to perform the analysis and fulfill the research aims (see, for example, Narayan and Sharma (2015), Narayan, Ahmed, and Narayan (2015), Bannigidadmath and Narayan (2016), Umar, Kenourgios and Papathanasiou (2020), among others). According to Narayan and Sharma (2015) and Narayan, Ahmed, and Narayan (2015), the results of hypothesis tests could be data frequency dependent. According, for example, to Bannigidadmath and Narayan (2016) or Umar, Kenourgios and Papathanasiou (2020), daily data frequency is better (compared to monthly, quarterly or weekly data) when the research aim is to retrieve as much information as possible from that data. As we aim to perform a continuous assessment of the connectivity between sustainable investment segments, it is important to have as much information as possible. Given this, we used daily data in our research. The daily values of the various variables studied were transformed into return series, $r_t =$ where $P_t$ and $P_{t-1}$ represent the daily values of a given series, on days $t$ and $t$-$1$, respectively.

The environmental stock indices used were selected due to data availability. To perform the analyses, all the time series should have a similar number of observations, which conditioned the beginning date (2009) and justifies the period considered. On the other hand, the conflict between Russia and Ukraine has been causing knock-on effects worldwide and seems to have triggered, among others, an energetic crisis, constituting yet another challenge for world leaders concerning the use of other energy sources. Thus, we aimed also to cover this special period (the onset of the Russia-Ukraine war), justifying the end date of the data.

Furthermore, we selected the referred period because there was remarkable growth in socially responsible investment over the last two decades and because the selected period covers several major events (e.g. the end of the global financial crisis of 2007/2009, the ESDC of 2010/2011, the oil-price crash 2014/2015, the COVID-19 pandemic and the most recent Russia-Ukraine war) and these events impact volatilities of most assets, asset classes, sectors and countries, causing serious damage to investment portfolios (Engle and Campos-Martins 2023). Therefore, an appropriate evaluation of the connectedness among different indices (representative of environmental and global financial investment) may be beneficial for investors and policymakers in their decision-making processes during extreme events.

### 4.2. Methodology

Several methods (e.g. correlation, VAR, VECM, Granger causality, and GARCH models, among others) have been applied to evaluate the stock market correlation, being its selection made according to the data availability and the study's goals. GARCH family models have been extensively used besides the other methods. Linear correlation measures, such as Pearson correlation, only allow the assessment of the overall correlation and do not consider the dynamic correlation (Das, Bhowmik, and Jana 2018). The Granger causality uses VAR models in the linear regression analysis and is a measure based on second-order, correlation-centered statistics, limiting its relevance to linear systems (Gencaga, Knuth, and Rossow 2015). The univariate GARCH model assumes that volatilities are constant among variables over the period, meaning that it is not able to capture correlations among multiple time series (Kenourgios and Samitas 2011). Although the constant conditional correlation GARCH model (CCC-GARCH) has removed the shortcomings of the univariate GARCH model, it also has shortcomings, as it considers correlation constant when it is, in reality, dynamic. In order to overcome this shortcoming, Engle (2002) developed a dynamic model (based on the CCC model) that considers that conditional correlation is time-varying. Other GARCH models have also been used to study volatilities and correlation of the stock markets returns (e.g. BEKK, VECH, EGARCH, MGARCH, GJR-GARCH, among others), with no clear superiority of any of them. Multiscale correlation approaches (e.g. continuous and discrete wavelet transformation models), which have the ability to study the relationship between stock markets in different time horizons and frequency bands (Hkiri et al. 2018), have been used in recent studies. The wavelet techniques allow for more complexity in the dynamics but at the expense of interpretability (Alexakis et al. 2021). Thus, given the referred, and as in this study we are only interested in daily data frequency (for the reasons already identified), we applied the DCC-GARCH model, which accounts for the time-varying nature of the conditional volatilities and correlations. Furthermore, compared with other volatility estimation models, the DCC-GARCH includes other explanatory variables in the mean equation to ensure the well specification of the model. At the same time, this model allows measuring the variance and the covariance of multiple variables directly, as it has the ability to augment multiple variables without adding too many parameters (Yahya, Abbas, and Lee 2023).

Given the complex behavior of financial markets, it is important to apply measures sensitive to non-linear interactions and relations. Furthermore, it is also important to quantify the information flow shared between different time series, which requires, according to Dimpfl and Peter (2014), time-series properties and an asymmetric measure. The TE introduced by Schreiber (2000) allows this assessment, regardless of the used model (Korbel, Jiang, and Zheng 2019), i.e. in a model-free approach. At the same time, it does not depend on data structure or linearity and is robust to spurious 'couplings', being in this sense, a non-parametric method. All of this led us to apply the TE approach.

Furthermore, as far as we know, this study is the first one to combine the selected approaches to investigate the connection between several representative indices of the environmental segments vis-á-vis two indices representative of the uncertainty in the stock markets together and a macroeconomic variable.

#### 4.2.1. DCC-GARCH

To fulfill the research aims, we applied a multivariate dynamic correlation model (DCC-GARCH) to model volatility and to construct dynamic conditional correlations on a rolling-window analysis. This model allows us to monitor the correlations generated over time, has comparative advantages and solves the problems found, due to the presence of a large number of free parameters, when the BEKK and VECH models were applied. The DCC model is easier to estimate and is comparatively more robust. Its main advantages are the positive definiteness of the conditional covariance matrices and the ability to estimate time-varying volatilities, covariances, and correlations among the assets parsimoniously (Yousaf and Ali 2020). According to Ciner, Gurdgiev, and Lucey (2013), it is (among other restricted correlation models, such as the Asymmetric Dynamic Conditional Correlation (ADCC) and the Corrected Dynamic Conditional Correlation (cDCC)) appropriate to evaluate the time-varying correlations between financial products and economic variables and have been applied in previous studies covering crisis and noncrisis periods (Sadorsky 2012; Yousaf and Ali 2020). Engle (2002) and Tse and Tsui (2002) proposed the DCC-GARCH model, which differs from other models, such as the constant conditional correlation (CCC), by allowing the conditional correlation matrix to be variable over time.

The estimation of this model involves two steps. In the first step, univariate GARCH models are applied to each series. In the second stage, the conditional correlation is generated starting from the standardized residuals obtained in the first stage.

In the DCC-GARCH model, the conditional covariance matrix is written as:

$$\sum{}_t = D_t \Gamma_t D_t \tag{1}$$

Where:

$$D_t = diag\left(\sqrt{h_{11,t}}, \sqrt{h_{22,t}}, \ldots, \sqrt{h_{nn,t}}\right) \tag{2}$$

$$\Gamma_{t+1} = [\mathrm{diag}(Q_t)]^{-1/2} Q_t [\mathrm{diag}(Q_t)]^{-1/2} \tag{3}$$

$$Q_t = (1 - \alpha - \beta)\overline{Q} + \alpha u_{t-1} \hat{u'}_{t-1} + \beta Q_{t-1} \tag{4}$$

$h_{it}$ follows a GARCH (1,1) process, $\sum_t$is the conditional covariance matrix and $u_t$is the vector of standardized values of $t$, $\Gamma_t$ is the time-varying correlation matrix, $Q_t$ is a positive semidefinite symmetric matrix, and $\overline{Q}$ is the non-conditional variance matrix in $u_t$. The time-varying elements of $\Gamma_t$,$\rho_{ij,t}$ are:

$$\rho_{ij,t} = \frac{q_{ij,t}}{\sqrt{q_{ii,t} + q_{jj,t}}} \tag{5}$$

Where $q_{ij,t}$ is an element of $Q_t$. For the positive definition of $\Gamma_t$, the matrix $Q_t$ must be positive definite. It is expected that $\alpha \geq 0$, $\beta \geq 0$ and $\alpha + \beta < 1$, for the conditional correlation matrix to be positive definite.

Estimation of the parameters of the DCC-GARCH model uses maximum likelihood estimation (MLE) on the assumption that the errors are normally distributed; the maximization function is:

$$L(\theta) = -\frac{1}{2}\sum_{i=1}^{T} n\log 2\pi + 2\log|D_t| + \log(\Gamma_t) + u'_t \Gamma_t^{-1} u_t \tag{6}$$

#### 4.2.2. Transfer entropy

The TE is an alternative to traditional causality assessments (Huynh et al. 2020). Despite the similarities between Granger causality and TE, this is a model free from restrictive assumptions, namely normality and linearity, being also robust to spurious relations (Lizier et al. 2011). In a financial context, according to Dimpfl and Peter (2014), specific time-series properties and an asymmetric measure are required to quantify the information flow. Thus, Schreiber (2000) proposes a measure of the information flow based on the Shannon entropy and more specifically, on mutual information, TE:

$$TE_{YX}(k, l) = \sum_{x,y} p(y_{t+1}, y_t^{(k)}, x_t^{(l)}) loglog \frac{p(y_t^{(k)}, x_t^{(l)})}{p(y_t^{(k)})} \tag{7}$$

Eq. (7) is a directional measure of the dependence between two variables (see, for example, Behrendt et al. 2019), derived for discrete data, and that requires estimating joint and conditional probabilities. However, most economic time series are continuous, thus continuous data have to be discretized and may be done using a finite number of partitions and symbolic codification (Behrendt et al. 2019). The presence of information flow may be tested using the bootstrap method proposed by Dimpfl and Peter (2013).

We also use net TE, given by $NET\ TE_{YX} = TE_{YX} - TE_{XY}$, in order to identify which of the variables in each pair is a net influencer or net influenced by the other. The dominant direction of the information flow will be: i. from $Y$ to $X$, if $TE_{Y \to X}(k,l) - TE_{X \to Y}(k,l) > 0$; ii. from $X$ to $Y$, if $TE_{Y \to X}(k,l) - TE_{X \to Y}(k,l) < 0$; iii. equal form $Y$ to $X$ as from $X$ to $Y$, if $TE_{Y \to X}(k,l) - TE_{X \to Y}(k,l) = 0$, meaning the flows are equivalent in terms of dominance.

The TE has been widely used in several research fields (see, for example, Marriott Haresign et al. (2022), Naef, Chadha, and Lefsrud (2022), and Fidani (2022), among many others). Here we focus on economics and finance, highlighting some work: Kwon and Yang (2008), Dimpfl and Peter (2013), Sensoy et al. (2014), Kim et al. (2020), and Ferreira et al. (2021).

In order to evaluate the dynamics of the relationship between indices, we employed a sliding windows approach based on windows of 1000 observations (i.e. about four years), allowing for a time-varying analysis of the behavior between variables. In crises or given events, it will be possible to identify the way in which those events affect the bidirectional relationship between indices. All the estimations of the TE were made using the R package RTransferEntropy.

## 5. Preliminary results

### 5.1. Descriptive analysis

Table 1 presents the main descriptive statistics of the daily returns of the variables under investigation. All the return series show signs of deviation from the normality hypothesis, considering the asymmetry and kurtosis coefficients. Except for the EPU and VIX indices, the skewness coefficients are negative, in line with Umar, Kenourgios and Papathanasiou (2020). The kurtosis coefficients are high, symptomatic of heavy tails, also in line with the finding of Umar, Kenourgios and Papathanasiou (2020). The Jarque-Bera (JB) test confirmed the signs of deviation from the normality hypothesis, rejecting the null hypothesis ($H_0$) of normally distributed return series, also corroborating Umar, Kenourgios and Papathanasiou (2020).

While the Ljung–box test, performed up to the 20 lag, shows significant linear and nonlinear dependency for all the return series, the ARCH test reveals heteroskedastic return series. Aiming to evaluate stationarity in the return series, we perform the traditional Augmented Dickey-Fuller (ADF) test, the results being shown in Table 1. The null hypothesis ($H_0$) states the return series have a unit root (i.e. the series are order 1 integrated, I(1)) while the alternative hypothesis ($H_a$) states the return series have no unit root or are order 0 integrated, I(0). The $H_0$ was rejected at a 1% significance level for all the return series, meaning they are I(0).

## 6. Main empirical results

### 6.1. Dynamic conditional correlations analysis

We aim to evaluate the short-term dynamics between environmental segments and global risk factors. From the logarithmic return series and considering the ADF test results presented above (Table 1), a multivariate model of conditioned heteroscedasticity

**Table 1.** Return series descriptive statistics.

| . | AE | EE | GB | PP | SW | Brent | DJ | EPU | VIX |
|---|---|---|---|---|---|---|---|---|---|
| **Mean** | −0,00001 | 0,00074 | 0,00034 | 0,00053 | 0,00039 | 0,00031 | 0,00053 | 0,00027 | −0,00032 |
| **Median** | 0,00026 | 0,00085 | 0,00061 | 0,00105 | 0,00068 | 0,00064 | 0,00073 | −0,00697 | −0,00696 |
| **Maximum** | 0,08875 | 0,12396 | 0,09553 | 0,06981 | 0,08402 | 0,41202 | 0,08983 | 3,21562 | 0,76825 |
| **Minimum** | −0,11400 | −0,12630 | −0,12463 | −0,15520 | −0,12513 | −0,64370 | −0,12922 | −3,14833 | −0,35059 |
| **Std. Dev.** | 0,01574 | 0,01579 | 0,01294 | 0,01435 | 0,01281 | 0,02829 | 0,01147 | 0,48286 | 0,07816 |
| **Skewness** | −0,34281 | −0,13115 | −0,81526 | −0,59698 | −0,47774 | −2,84641 | −0,69924 | 0,04238 | 1,13617 |
| **Kurtosis** | 7,26985 | 10,24778 | 16,30695 | 9,16695 | 11,76174 | 109,99363 | 15,98606 | 5,22858 | 9,37222 |
| **JB (Prob.)** | (0,0000) | (0,0000) | (0,0000) | (0,0000) | (0,0000) | (0,0000) | (0,0000) | (0,0000) | (0,0000) |
| **ADF (Prob.)** | (0,0000) | (0,0000) | (0,0000) | (0,0000) | (0,0000) | (0,0000) | (0,0000) | (0,0000) | (0,0000) |
| **Q (20)** | (0,0000) | (0,0000) | (0,0000) | (0,0000) | (0,0000) | (0,0000) | (0,0000) | (0,0000) | (0,0000) |
| **$Q^2$ (20)** | (0,0000) | (0,0000) | (0,0000) | (0,0000) | (0,0000) | (0,0000) | (0,0000) | (0,0000) | (0,0000) |
| **ARCH (1)** | (0,0000) | (0,0000) | (0,0000) | (0,0000) | (0,0000) | (0,0000) | (0,0000) | (0,0000) | (0,0000) |

(DCC-GARCH) was estimated. The DCC-GARCH model estimation involved several specifications, namely, the inclusion of asymmetric effect, the size of the lag and the statistical distribution of errors. The specific assumptions of the models were always respected, and considering the Schwarz and Akaike information criteria, the simplest DCC-GARCH model version was selected, as it was the model that minimized the referred criteria and that revealed the best fitting. To test the robustness of the GARCH model estimates, other alternatives were estimated, namely the ADCC, cDCC, DCC-DECO, and cADCC variants, as well as testing various specifications involving the distribution of errors and the lag size. However, in none of the cases did the conditional correlations change significantly, which helps us to believe in the robustness of the estimates obtained with the selected model. Table 2 presents the results.

Globally, we can see that the parameters estimated by the model are statistically significant. Furthermore, the sum of the global parameters of the model ($\alpha + \beta < 1$) is close to one, ensuring that the conditional correlation matrix is defined as positive, in accordance with the methodological proposals of Engle (2002) and Tse and Tsui (2002). Consequently, the volatility generation process is considered stable and shows a high degree of persistence, with the effects of shocks persisting for long periods, as if the analyzed variables had a memory of market events.

As more recent studies point to the need to evaluate the relationship between environmental stock indices vis-à-vis the traditional stock market and global risk factors in a dynamic way (a time-varying analysis), we aim to cover this gap.

Figure 1 was constructed based on the multivariate model estimates. It allows following the conditional correlations over time between environmental indices and global risk factors. The graphic analysis of the dynamic conditional correlations generated between the environmental segments allows us to conclude that they present a high variability over the period under analysis. In most cases, the pairs of correlations showed average values greater than 0.6, this was the case for the EE/PP (0.63), EE/SW (0.64) and PP/SW (0.65) pairs. The intensity levels of the correlations were over 0.85, especially from 2009 to 2011, possibly due to the turbulent environment generated by the global crisis and sovereign debts. It is also important to highlight a significant increase in the levels of correlation intensity, especially from February 2020, which may be due to the most recent pandemic crisis outbreak. When comparing the average conditional correlations recorded in March 2022 with February of the same year, some pairs of correlations

**Table 2** . Estimates of the DCC-GARCH model.

| | AE | EE | GB | PP | SW | WTI | DJ | EPU | VIX |
|---|---|---|---|---|---|---|---|---|---|
| $\alpha_0$ | 0,0003 | 0,0006 | 0,0005 | 0,0007 | 0,0005 | 0,0005 | 0,0008 | 0,0045 | −0,0003 |
| | (0,1169) | (0,0007) | (0,0005) | (0,0005) | (0,0014) | (0,1018) | (0,0000) | (0,5007) | (0,7845) |
| $\alpha_1$ | 0,0000 | 0,0000 | 0,0000 | 0,0000 | 0,0000 | 0,0000 | 0,0000 | 0,1016 | 0,0012 |
| | (0,0001) | (0,0000) | (0,0000) | 0,0003 | (0,0000) | 0,0001 | (0,0000) | (0,0000) | (0,0000) |
| $\gamma_1$ | 0,0958 | 0,0934 | 0,1157 | 0,0635 | 0,0981 | 0,1131 | 0,1674 | 0,3013 | 0,1755 |
| | (0,0000) | (0,0000) | (0,0000) | (0,0000) | (0,0000) | (0,0000) | (0,0000) | (0,0000) | (0,0000) |
| $\beta_1$ | 0,8981 | 0,9009 | 0,8782 | 0,9274 | 0,8747 | 0,8843 | 0,8072 | 0,2792 | 0,6200 |
| | (0,0000) | (0,0000) | (0,0000) | (0,0000) | (0,0000) | (0,0000) | (0,0000) | 0,0009 | (0,0000) |
| $\alpha$ | 0,0100 | | | | | | | | |
| | (0,0000) | | | | | | | | |
| $\beta$ | 0,9876 | | | | | | | | |
| | (0,0000) | | | | | | | | |
| $\alpha + \beta$ | 0,9976 | | | | | | | | |

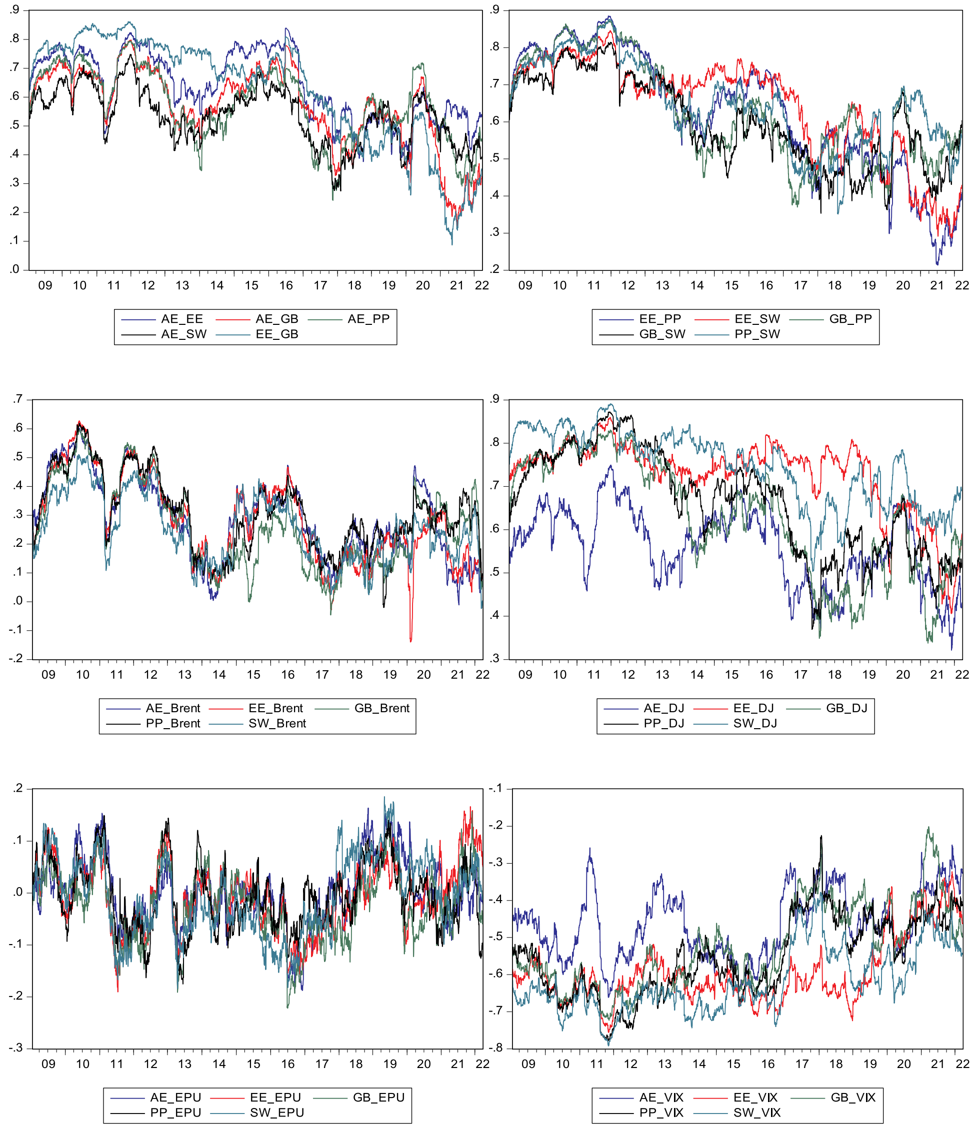


**Figure 1.** Dynamic conditional correlations.

recorded quite significant average increases. This was the case with the AE/GB and EE/GB pairs, for example, which recorded average increases of 42% and 58%, respectively. Considering the results obtained, which are in line, for example, with the ones of Umar, Kenourgios and Papathanasiou (2020), it is possible to conclude that the established dynamics among environmental segments translate into similar responses to market events, especially in times marked by high volatility.

Considering the conclusions of other studies, namely Mandigma (2014), Gabriel and Manso (2014), Gabriel and Pazos (2017, 2018), and Umar, Kenourgios and Papathanasiou (2020), among others, in which the links between some of the main traditional investment indices were analyzed, it is possible to conclude that, similarly to what happens between this type of indices, environmental indices also maintain relatively close behavior patterns. Additionally, the dynamic correlations generated between the environmental indices and the benchmark index of traditional markets, the DJ, proved to be quite high, approaching 0.9, which allows us to conclude that environmental investment is not immune to occurrences in investment. Moreover, as suggested by Mandigma (2014), Gabriel and Manso (2014), Gabriel and Pazos (2018), Tsai (2014), Akhtaruzzaman et al. (2021), Kang and Lee (2019), Umar, Kenourgios and Papathanasiou (2020), the US market is a driver of stock markets in general.

Perhaps this proximity between stock markets 'in general' will find an explanation in the phenomenon of financial globalization, which has created favorable conditions for interaction and contagion between markets, making the process of investment diversification difficult.

In analyzing the links maintained between the environmental segments and variables of a global nature, namely the EPU and VIX indices, it is important to highlight two different situations. Regarding the first index, the results obtained did not fully confirm the conclusions of other research involving traditional indices, namely Christou et al. (2017), Guo, Zhu, and You (2018), Hu, Kutan, and Sun (2018), Phan, Sharma, and Tran (2018), Xiong, Bian, and Shen (2018) and Wang, Li, and He (2020), as the EPU index did not always maintain a negative correlation with environmental investment. As for the VIX index, it showed negative correlations with the environmental segments, confirming the conclusions obtained in other research (Guo and Whitelaw 2006; Sarwar 2012; Basher and Sadorsky 2016; Shu and Chang 2019, among others). This variable may probably be considered a kind of risk factor for environmental investment.

### *6.2. Transfer entropy dynamic analysis.*

We applied a sliding windows approach considering consecutive windows of 1000 observations, i.e. calculating the TE for the window from $t = 1, \ldots, 1000$, then for $t = 2; \ldots; 1001$, and so on, for a total of 2297 estimates for TE for each pair under analysis. Were used windows of 1000 days in length as it allows for a reasonable compromise between capturing relevant historical data and keeping the computational burden manageable, and because this window length provides more historical context and produces more robust results than smaller windows. This analysis allows us to identify the time-varying dynamics of the TE and the NET TE. Figure 2 shows the evolution of TE between the AE index (an environmental index) and all four indices representing global risks (DJ, Brent, EPU, and VIX). Figure 2 also shows each pair's reverse TE and the NET TE. From Figure 2(a), we can see that the AE transmits more information to DJ than it receives from it almost all the time, although this pattern changed after late 2020. Figure 2(b) shows that the AE receives more information from Brent than it transmits to it almost all the time. The exceptions occurred between the middle of 2014 and 2015 (which may be related to the oil-price crash of July 2014 – December 2015 (Alexakis et al. 2021)), a few months in the third quarter of 2016, and after the beginning of 2020 until the end of the analyzed period (coincident with the COVID-19 pandemic crisis, and also with the armed conflict between Russia and Ukraine). The AE receives more information from the EPU and VIX indices up to early 2016 than it transmits to them, the pattern changing after that (as shown in Figure 2(c,d). The former (EPU) became a

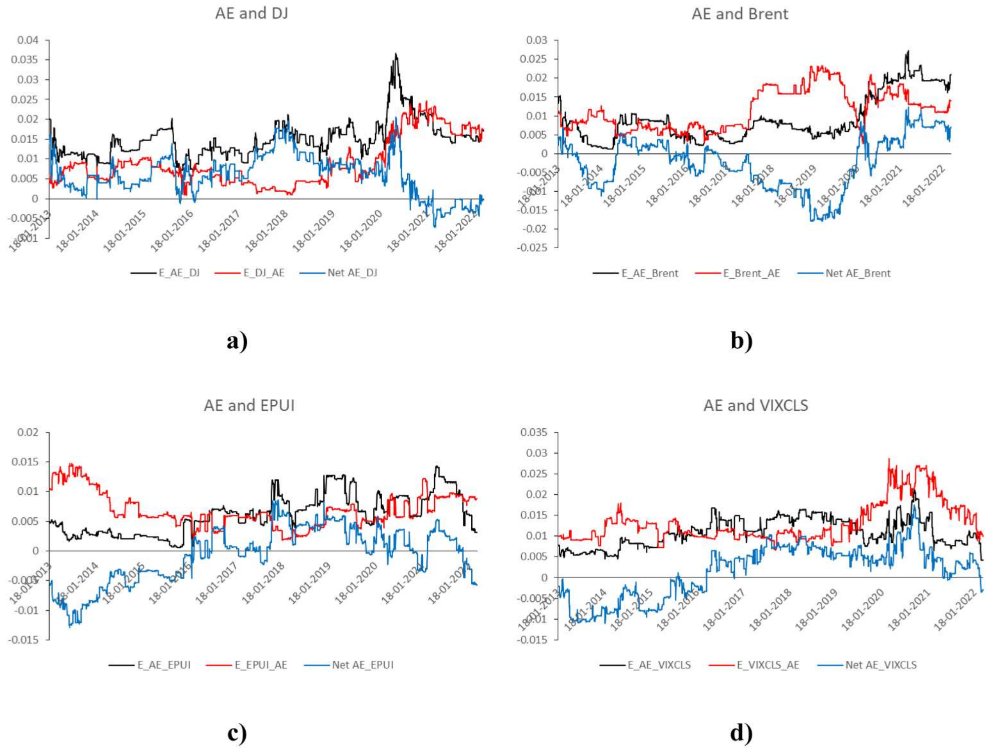


**Figure 2.** Time-varying TE and NET TE between AE index and: (a) DJ; (b) Brent; (c) EPU and (d) VIX. Note: The analysis was made using a sliding windows approach with a window size of 1000 observations.

receiver again in late 2020, early 2021 and early 2022. The latter (VIX) only became a receiver again in early 2022, which may be justified by the onset of the conflict between Russia and Ukraine, corroborating Umar, Polat, et al. (2022), to whom the war between Russia and Ukraine have changed the relationship between financial markets.

We made a similar analysis of all sets of paired indices. However, due to space constraints, we do not show the whole set of paired TEs here, but the results can be supplied upon request.

The TE satisfies the additivity property. Thus, to make viewing and interpreting of information easier, we transformed the whole set of TE estimates into yearly-based heatmaps (all the heatmaps are built based on information as displayed in Figure 2), calculating the mean yearly NET TE (see Figure 3).

Analyzing all the heatmaps makes it possible to identify time-varying patterns but without a specific or common pattern. However, a change has been seen in the level of color intensity in all the heatmaps since 2020. This means there is a higher information flow between the analyzed indices, consequently more interdependence between them, and a similar response to market events, especially at times of high volatility, in line with Mirza et al. (2023). This evidence aligns with the previously applied method, giving robustness to the analysis developed.

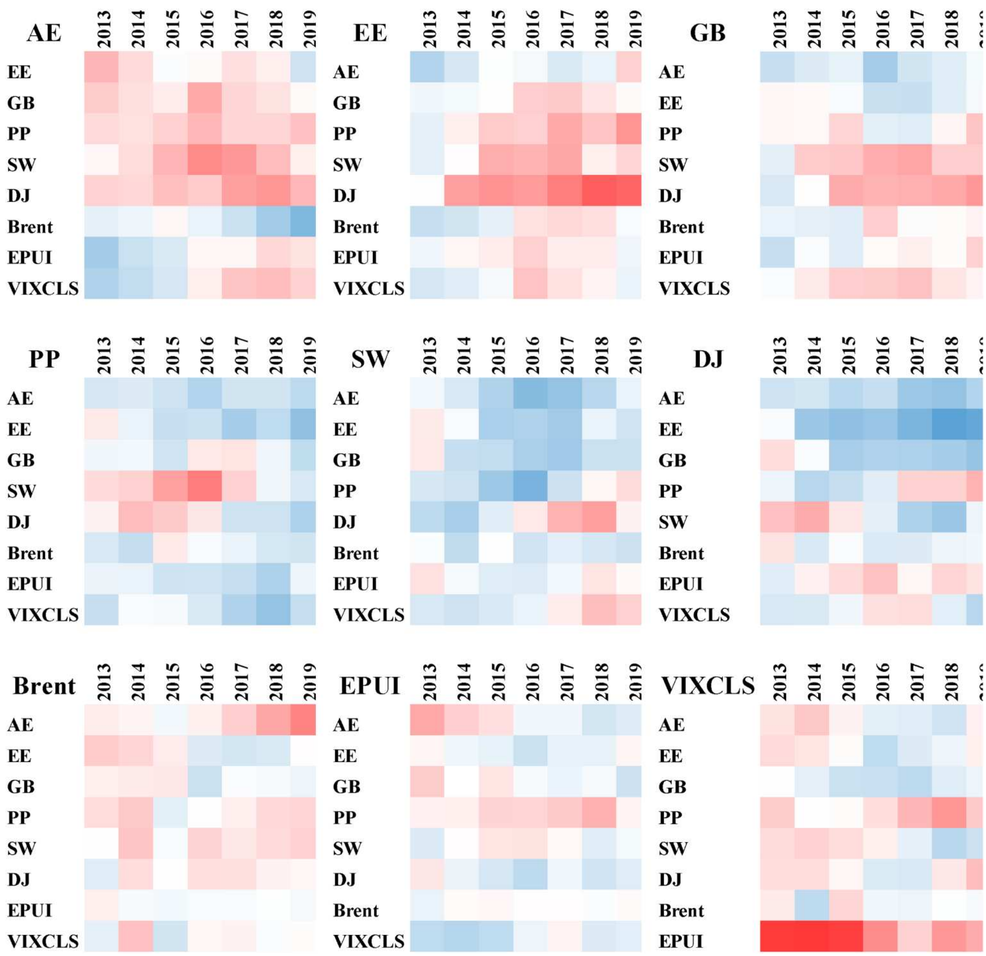


**Figure 3.** Yearly evolution of the NET TE. Notes: (i) Each heatmap has the basic index represented in the top-left cell; (ii) The blue cells correspond to negative NET TE values meaning the index is net influenced; (iii) The red cells correspond to positive NET TE values meaning the index is a net influencer.

The AE plays a fundamental role between the environmental indices, being the most influential of all, influencing them almost all the time. An exception was found for the EE and PP indices, the former in 2019 and 2020, and the latter in 2020 and 2021. In addition to the environmental indices, the AE influences the DJ during all the analyzed periods, except after 2020. Conversely, the AE is highly influenced by Brent until 2020 (less between 2014-2015, maybe due to the oil-price crash of July 2014 – December 2015) and by the EPU and VIX indices mainly until 2016 (this may be related to the ESDC which begins shortly before the Greek bailout in 23rd April 2010 and extended until the exit of Cyprus from the economic adjustment program in March 2016 (Alexakis et al. 2021)). In 2020, Brent prices achieved negative values, which could explain the changing pattern between AE and Brent in 2020. After 2019, the PP index changed its pattern and became an influencer of the remaining environmental indices and of the DJ, Brent, and EPU. The PP index was also the most influential environmental index of Brent after 2019. Considering the PP index composition and mobility restrictions imposed by the COVID-19 pandemic (after 2019), the companies forming the index could have reduced fossil combustible consumption, which indirectly could have improved the revenue from less polluting products. It is also curious to see that after 2019 all the environmental indices, especially the EE, PP and SW indices, became influencers of the GB index.

After 2020, the DJ index changed its influence pattern in almost all the environmental indices (except for the PP index). It became an influencer of all of them, suggesting that environmental investment is not immune to occurrences in investment. This changing pattern may reflect the turmoil faced by financial markets due to the COVID-19 pandemic. Probably due to this turmoil, the Brent price was pushed to minimum values during March and April 2020 (in this period, the WTI oil prices declined to negative territories for the first time), and Brent became strongly influenced by the DJ from 2020, and by the majority (except EE and PP indices) of the environmental indices. At the same time, as the DJ is a stock index that tracks 30 of the largest US companies, it seems that environmental indices became more exposed to the major international capitalizations after 2020.

The VIXCLS index heatmap is clearly the one marked with more red cells. This means that it influences all the other indices more than they influence it, being the most influential of the analyzed indices (in line with the findings of Umar, Kenourgios and Papathanasiou (2020)). The VIXCLS index has been considered in several studies as predicting stock market behaviour. Thus, given its net influence in almost all the indices and during almost all the period, the VIXCLS can be used for investors to predict the remaining indices' behavior. Given there are more red cells in the VIXCLS index heatmap than in the EPU index, the former exerts more net influence on all the environmental indices, corroborating Umar, Kenourgios and Papathanasiou (2020). This evidence suggests, first, that the market volatility is more informative than the economic policy uncertainty for environmental investment. Secondly, environmental investment is not immune to market volatility. These findings are in line with Shu and Chang (2019).

The EPU index heatmap is found to have the lowest color intensity, blue being the dominant color. This means there is less liquid information flow from economic policy uncertainty to the remaining indices, corroborating Umar, Kenourgios and Papathanasiou (2020). Thus, environmental indices, especially the GB and PP indices after 2019, could be used for diversification in times of economic policy uncertainty.

Globally, the pandemic crisis seems to play a major role in the relationship between the several environmental segments of stock markets. Considering the influence of environmental stock markets and risk factors on each other, the AE is the most influential environmental stock market segment, on the other hand, VIXCLS is the most influential global risk factor, especially in highly volatile periods, corroborating Umar, Kenourgios and Papathanasiou (2020), who identified the VIXCLS as a significant transmitter of spillover effects to other markets, meaning that the remaining indices are greatly influenced by the level of uncertainty as calculated by this index.

## 7. Conclusions

This research analyzed the connections and transmission of information between environmental stock market segments, seeking to identify the existence of risk transmission channels. Using a sample of thirteen years, the study employed a multivariate model of conditioned heteroscedasticity and non-parametric econophysics models based on TE. The findings suggest that environmental segments have similar behavior during times of high volatility, such as those related to the GFC and the COVID-19 pandemic crisis, indicating close links among them. It was also possible to identify AE as the most influential environmental stock market segment. The VIXCLS acts as the most influential global risk factor, not only in the environmental stock market segment but also in the remaining risk factors (especially in crisis periods) and traditional investment index, meaning that the environmental stock market segments and the remaining risk factors are greatly influenced by the level of uncertainty as calculated by the underlying index. Thus, we are led to conclude there is no differentiated behavior between environmental indices and the traditional index (represented by the DJ).

The obtained results are consistent with the existing literature and theoretical expectations, highlighting the importance of understanding the interplay between environmental and traditional investment options in the context of global financial markets. The results are economically significant as they provide insights into the interconnectedness of stock markets (over time, international stock markets have become more closely connected, and the diversification opportunities for investors have decreased), the impact of global risk factors on environmental investment (the global risk factors, such as the EPU index and the VIX, can have different relationships with environmental stock indices compared to traditional stock indices), and the dynamics of sustainable investment segments (the behavior of environmental indices is not entirely different from traditional indices, and the environmental indices are influenced by market events, including global risk factors).

The results have important implications for various market participants, including investors, portfolio managers, policymakers, and regulators. Investors and portfolio managers interested in environmental assets can use the connectivity results to make more informed investment decisions and construct their portfolios. However, the benefits of diversification using environmental assets diminish during turbulent periods, so investors should consider incorporating other types of assets and hedging instruments to mitigate risks. During market volatility, a diversified approach may offer more stable returns. Portfolio managers should strive to optimize the risk-return balance in their investment strategies by understanding the dynamic correlations between environmental stock market segments and global risk factors. These findings are also relevant for policymakers and regulators as they need to consider the risk of contagion in environmental stock market segments and design appropriate regulatory frameworks to reduce market volatility and ensure financial stability during uncertain times.

In future research, we intend to look deeper into the possibilities of environmental assets in the formation of investment portfolios and in risk management, combining socially responsible assets with traditional assets, using not only optimization models but also other risk measures, such as the COVOL recently proposed by Engle and Campos-Martins (2023).

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The authors report there are no competing interests to declare.

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## *Table A1. Indices and variables' description.*

| Index | | Description |
|---|---|---|
| **Alternative Energy** | **AE** | Includes developed and emerging market large, mid and small-cap companies that derive 50% or more of their revenue from products and services in Alternative energy. It was launched on January 20, 2009. On February 28, 2022, it was composed of 80 constituents from the utilities, industrial, information technology, energy, and materials sectors. |
| **Energy Efficiency** | **EE** | Includes developed and emerging market large, mid and small-cap companies that derive 50% or more of their revenue from products and services in Energy Efficiency. It was launched on January 20, 2009. On February 28, 2022, it was composed of 59 constituents from the consumer discretionary, industrial, information technology, real estate, materials and utilities sectors. |
| **Green Building** | **GB** | Includes developed and emerging market large, mid and small-cap companies that derive 50% or more of their revenue from products and services in Green Building. It was launched on September 07, 2010. On February 28, 2022, it was composed of 83 constituents from the real estate and consumer discretionary sectors. |
| **Sustainable Water** | **SW** | Includes developed and emerging market large, mid and small-cap companies that derive 50% or more of their revenue from products and services in Sustainable Water. It was launched on January 20, 2009. On February 28, 2022, it was composed of 9 constituents from the utilities, industrial, information technology, and materials sectors. |
| **Pollution Prevention** | **PP** | Includes developed and emerging market large, mid and small-cap companies that derive 50% or more of their revenue from products and services in Pollution Prevention. It was launched on January 20, 2009. On February 28, 2022, it was composed of 6 constituents from the materials, consumer staples and industrial sectors. |
| **Brent** | **Brent** | Corresponds to the price of the Brent barrel in the international market. |
| **Dow Jones** | **DJ** | A stock index that tracks 30 of the largest US companies. It was launched on May 26, 1986, being one of the oldest stock indices. Its performance is widely considered a useful indicator of the entire US stock market. It covers all sectors except transportation and utility services. |
| **Economic Policy Uncertainty** | **EPU** | Created in 2016 by the three US economists, Scott R. Baker, Nicholas Bloom, and Steven J. Davis, it is based on newspaper coverage frequency as a proxy for economic policy uncertainty. It is computed by counting news articles containing pre-defined keywords related to policy-making and economy and conveying uncertainty. It covers news from 10 large US newspapers (USA Today, the Miami Herald, the Chicago Tribune, the Washington Post, the Los Angeles Times, the Boston Globe, the San Francisco Chronicle, the Dallas Morning News, the New York Times, and The Wall Street Journal). It represents stock market uncertainty, based on the analysis of newspaper news. |
| **Cboe Volatility Index** | **VIX** | |

(*Continued*)

Continued.

| Index | Description |
|---|---|
| | It measures the market's expectations of near term volatility conveyed by S&P 500 stock index option prices. Introduced in 1993 by Robert E. Whaley, it is a financial benchmark designed to be an up-to-the-minute market estimate of the expected volatility of the S&P 500 Index. It is calculated using the midpoint of real-time S&P 500 Index option bid/ask quotes. The components of the VIX Index are near – and next-term put and call options with more than 23 days and less than 37 days to expiration. |