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Modeling Synchronization Risk among Sustainable Exchange Trade Funds: A Statistical and Network Analysis Approach

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Abstract: We evaluate the environment, society, and corporate governance rating (ESG rating) contribution from a new perspective; the highest ESG rating mitigates the impact of unexpected change in the implied volatility on the systemic stock market risk. For this purpose, we use exchange-traded funds (ETF) classified by their ESG rating into quartiles to estimate the synchronization as a proxy by systemic risk. Then, for each ETF quartile, we study the effect of the implied volatility over the synchronization. Our study is the first to model sustainable ETFs' synchronization by combining econometric modeling and network methods, including 100 ETFs representing 80% of the global ETF market size between 2013 and 2021. First, we find that a higher ESG rating mitigates the effect of implied volatility over ETF synchronization. Surprisingly, the effect is the opposite in the case of ETFs with lower ESG ratings, where an increase in the volatility expectation increases the synchronization. Our study depicts the effect of sustainable ETFs on lessening the systemic risk due to returns synchronization, this being a novel contribution of this asset class. Finally, this paper offers extensions to deepen the contribution of other asset classes of ETFs in terms of their synchronization behavior and impact on risk management and financial performance.

Keywords: ETF; ESG ratings; risk management; econometric modeling; network analysis; volatility shocks; financial market synchronization

MSC: 91B05; 91G45; 91G70

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1. Introduction

During the last years, we observed the demand for the financial system to be part of climate and social action through new standards for the management of business, investments, and the statement of public information reformulated through the environment, society, and corporate governance (ESG) quality criteria. The ESG parameters include environmental, social, and governance factors in the investment decision-making process as crucial elements of governments' and regulatory institutions' goals, which nowadays are a critical component for the most relevant asset managers worldwide [1]. Specifically, the environmental factor measures how a firm manages its impacts on the environment. Social criteria capture how the company manages its relationships with its stakeholders. Additionally, governance captures the elements to protect the shareholders' interests.

Parallel to the extension of ESG in financial markets, ref. [2] observes that we have experienced an expansion in global economic and sociopolitical openness in the last two decades, which has determined greater financial integration. Major financial integration and economic openness generate a higher inter-connectedness and complexity in capital markets. As a result, to understand and model complex economic systems, it is necessary to consider and simplify multiple actors with many interaction rules of several degrees and non-linearities, among other characteristics [3]. For these reasons, there are advantages to using network approaches because, for example, it is feasible to estimate the distance between two components of the system together with how likely an indirect effect is between them that could be relevant to consider in a broad model.

Greater integration, in turn, requires better management of macroeconomic and financial risks, which have increased in importance given the more significant links between markets. This increase in the degree of connections and the number and diversity of financial assets argues the need for new methodologies that classify, prioritize, and analyze the complex dynamic reality of financial markets in an integrated and, simultaneously, simplified way. In this sense, network methods efficiently describe large complex systems collaborating to reduce dimensionality. Furthermore, the globalization of financial markets increased the number of investment products and lowered the entry barriers for investors worldwide. For instance, the supply of Exchange Trade Funds (ETF) in 2010 went from USD 1.3 billion in assets under management (AUM) to USD 7.7 billion in 2021 [4].

Moreover, the ETF industry accounted for 16 percent of U.S. stock market capitalization at the end of 2021, surpassing the 14 percent held by the mutual funds industry. The ETF example highlights a broad market phenomenon: a global financial market more integrated, interdependent, and connected [5]. Consequently, the returns between financial assets are more prone to be synchronized.

Synchronization phenomena relate to the co-movement of asset returns; their maximum levels being coincident with important economic shocks and high global equity market volatilities [6]. Hence, the synchronization for the equity markets is relevant because an increase in the co-movements of returns generates financial contagion on a large scale [2], even more when the interconnections among financial agents vary over time, countries, and regions [7], becoming a potential disturbing factor of instability among market participants and financial institutions such as mutual funds [8].

The utilization at present of ESG scores as inputs for decision making among the investment community is a pervasive behavior. Because of this, institutional investors such as mutual funds, pension funds, and ETFs, among others, make substantial efforts to include high-ESG assets in their investment portfolios and incorporate ESG scores as inputs for their decision-making process.

This ESG motivation is due to two reasons. First, growth in capital managed by high ESG funds has grown about twice as fast as low ESG funds. Ref. [9] notes that 11 months after Morningstar published the mutual fund sustainability ranking in March 2016, mutual funds with high ESG increased by USD 22 billion, while their peers with low ESG decreased by USD 12 billion.

Second, high ESG funds are less sensitive to withdrawals during periods of poor financial performance. Ref. [10] observes a negative (positive) correlation between outflows and past returns in mutual funds with low (high) ESG scores, indicating that investors are more likely to redeem fund shares with better performance while maintaining their fund quotas with poor results. This behavior shows that a high ESG score would increase investors' disposition effect [11].

The above evidence on ESG funds highlights the relevance of a better understanding of the attributes of a financial asset, its risks, and its financial performance. The relationship between a financial asset's return and its risk level not only influences its attractiveness as an investment vehicle but also influences its importance in belonging to investment portfolios, contributing to the adequate management of financial and corporate risks. The latter intertwined relationships are especially critical in complex systems such as today's global financial markets, characterized by a high level of interconnections, a high level of interactions, and greater exposure to systemic shocks, especially in contexts with imperfect and incomplete information. In these scenarios, risk monitoring and their econometric modeling are vital. For example, modeling the econometric relationship between the structure of assets and liabilities of banking institutions operating in Europe, Israel, the United States, and Canada, ref. [12] finds that their structure of assets and liabilities and, therefore, their risk management, have a strong influence on their performance and liquidity.

The rise in the volumes invested in high ESG assets generates interest in learning about its effects on the performance of capital assets such as stocks, bonds, mutual funds, and ETFs (see a summary in [13]). However, to the best of our knowledge, the literature related to understanding the influence of ESG on systemic risk provoked by the synchronization of returns is scarce. Deepening the monitoring and understanding of systemic risk is relevant to global financial stability and contagion risk under economic and financial turmoil. A broad strand of the literature evidences that global shocks provoke high levels of synchronization, increasing the correlations into the stock market and jeopardizing market stability, decreasing the benefits of diversification, and increasing the exposure of global investment portfolios to significant losses [14–18].

Our paper answers the following research question: Are there differences in the synchronization level between ESG equity ETFs funds with high and low scores? We conjecture that assets with a higher (lower) level of ESG are less (more) likely to sync during economic and financial shock events. In other words, assets with high (low) ESG present a lower (higher) synchronization of returns, allowing investors to diversify with lower (higher) effectiveness, especially during periods of high volatility and economic and financial turmoil.

Broadly, we test our hypothesis based on an empirical strategy that stands on network analysis and econometric models:

1. We use 100 global equity ETF equivalents at 80% of the global amount under management in this industry and classify these ETFs according to their ESG score in four quartiles. Specifically, we used the 2021 ESG score to rank the ETFs from the top ESG score to the bottom ESG score (ESG score for ETFs has been available since 2021 and is updated quarterly. Nevertheless, none of the ETFs included in this study changed quarterly between 2021 and 2022).
2. We built the ETF asset correlation network for each quartile to measure the ETFs' synchronization of returns over time.
3. We apply econometric modeling to study the statistical significance of the CBOE Volatility Index's (VIX) influence on this synchronization phenomenon.

We study systemic financial risk by applying network analysis, focusing on ETF market synchronization. Specifically, via this empirical strategy, we test the effects of volatility spillover shocks on the ETF market synchronization and the effect of the ESG rating on the ability of the ETF network to tolerate changes in the global level of volatility in financial markets. For this, we calculate the synchronization of returns between January 2013 and December 2021 using the length of the Minimum Spanning Tree (MSTL) and the length of the Planar Maximally Filtered Graph (PMFGL). In addition, to capture variation in the taxonomy of the ETF network, we measure relevant network parameters such as the diameter and strength. Finally, we estimate the relationship between VIX and our synchronization measures by applying regression models with Newey–West standard errors.

As the literature states, these methods properly model the aggregate behavior of complex systems characterized by interactions between many components. Thus, an asset represents a small component of the financial system, related simultaneously to the rest of the assets. Furthermore, considering that the size and diversity of financial assets and the influence of the financial system increased several times compared with previous decades [19], thus becoming more visible and easier to reach for new generations of investors, increasing the synchronized behavior among financial markets.

We hypothesize that high ESG ETFs will synchronize less than low ESG ones under rising expected market volatility. We think this behavior would occur because investors believe that assets with a high ESG can better confront the risks that underlie an increase in implied volatility, which is commonly related to economic and financial crises [19]. A second explanation relates to the affect heuristic, where feelings can give way to a more reasoned analysis of decisions and guide subsequent judgment and decision making.

Accordingly, the positive evaluation associated with the ESG score of a financial asset could influence a positive evaluation regarding its behavior in difficult times such as financial, economic, or any other shock or crisis that tends to raise the implied volatility of the financial markets [9,20,21]. Finally, the influence of non-pecuniary motives could also affect investors. In this sense, investors consider environmental and social factors in their decision making, causing them to be less reactive to selling high-ESG investments in times of financial instability compared with low-ESG investments [22–27].

In this sense, this research contributes to studying correlations using network methods in the ETF funds' industry categorized according to their ESG level to understand their synchronization behavior under unexpected shocks in the implicit volatilities in global equity markets. Specifically, the evidence in this paper is novel and valuable in three ways:

1. We present a new approach to the influence of ESG on the performance of financial assets, complementing the studies that study profitability and risk. Indeed, we focus on systemic or contagion risk, using the synchronization of financial markets as a proxy for the potential danger of contagion of adverse shocks to investment portfolios.
2. Using ETFs has two advantages: (i) ETFs allow us to work with their market return and systemic risk, allowing us to study changes in the value perceived in the fundamentals of each asset in the fund and changes in the market sentiment regarding the ETF. (ii) ETFs today are the investment vehicle with the most significant expansion in the financial market regarding assets under management. According to official figures from Statista, by 2022, the 2010 AUM went from USD 1.3 billion to USD 7.7 billion.
3. We apply financial network methodologies to improve the aggregate understanding of a complex phenomenon such as synchronization and its impact on a highly relevant financial asset class that rapidly adopts ESG standards on its investment policies.

The novelty of the study is not only related to the method used but instead the description of the resulting graph tree as a measure of a general correlation between assets (in the paper, ETFs synchronization), which corresponds to the length of the MSTL. This characteristic, which shows the correlation between ETFs in a given period, is the basis for econometric models to test the hypotheses. In this sense, unlike other studies that use network measures, they focus on the description of the system, while in this study, we use them to model the phenomenon of synchronization between ETFs.

The paper has five sections. In Section 2, we review the literature. Section 3 details the methodology. In Section 4, we present the results. In Section 5, we discuss our results. Finally, in Section 6, we show the conclusions.

2. Theoretical Background

2.1. Network Methods and Financial Markets

Both the theoretical and empirical literature remarks financial markets behave as a complex system (See more details in Appendix A), ascertaining that their behavior and their reaction to disturbances and shocks resemble the behavior of complex systems. As a tool to model complexity, there are multiple applications of network models in financial markets. Works applying network models focus on the implications of network properties on the financial stability and fragility of capital markets [28,29]. Furthermore, there are studies that explored how the distribution of the links of a network affects the systemic reaction to shocks and how the connectivity of critical nodes could destabilize the system [30–33]. Likewise, other recent works focus on topics related to transaction networks of financial assets, portfolio strategies, financial risk, forecasting, and financial crises [8,34–40].

2.2. Systemic Risk and Financial Markets Synchronization

Systemic risk corresponds to the probability of financial contagion caused by sequential defaults on debt payment obligations, derivatives, and credits [41–44]. Alternatively, financial contagion is due to losses caused by generalized decreases in the market prices of financial assets and investment instruments. Fire sales generate these losses and fund runs and massive sales derived from the classical fly-to-quality behavior of financial agents under market turmoil [45].

Market synchronization is critical in the systemic risk derived from financial losses. Indeed, a significant drop in the price of an asset has different effects if it occurs at times of high or low synchronization and when the market is under a bearish or bullish trend. Thus, if an asset price falls when the market is highly synchronized, the probability that this fall spreads to a large part of the market network is high (low), especially when the market's tendency is low (high). On the contrary, if this drop occurs at times of low synchronization, it will likely extend only to assets that present a high (low) correlation with it, especially when the tendency of the aggregate market is high (low).

The literature uses network analysis to measure synchronization using Minimum Spanning Tree (MST) and Planar Maximally Filtered Graph (PMFG) [37,46], which allows visualizing the asset returns regarding the rest of the market and their degree of co-movement through time. In this regard, ref. [47] observed that the episodes of high synchronization of financial markets coincide with the collective behavior of investors, especially when the market shows marked trends. For instance, evidence indicates that during synchronization of returns —when financial assets exhibit a similar upward or downward tendency—the network formed by financial assets belonging to the same asset class tends to display a change in its topology related to the "small-world" property [48].

Market connectedness plays a relevant role in the financial system's stability. According to [49], a connected network can, on the one hand, better absorb negative impacts and give the system greater robustness. On the other hand, however, this greater connectedness can also spread shocks and create greater financial fragility. Nonetheless, synchronization affects the cost of diversification of investment portfolios. Indeed, during periods of low synchronization, the costs of diversification are lower since fewer assets in the portfolio are enough to extract the maximum benefit from diversification. On the contrary, in periods of high synchronization, it is necessary to incorporate more assets in the portfolio to maintain diversification, increasing the transaction and administration costs [40].

2.3. Influence of ESG on Market Synchronization

In the current context of sustainable investing, responsible investors seek to either avoid or reduce exposure to investments that pose more significant ESG risks influencing companies to make them more ESG-friendly, and thus generate more positive benefits for society (See more details in Appendix B). Moreover, investors are willing to incorporate ESG considerations into the investment decision-making process for financial reasons. For instance, "doing well by doing good" is based on the expectation that ESG investing will enhance performance [13]. Accordingly, issuing companies, investment funds, and financial intermediaries must comply with information declaration protocols regarding their environmental, social, and corporate governance impact (ESG disclosure), giving investors and the financial community information to include in their decision processes.

Multiple factors explain the interest in sustainable investments. Ref. [50] indicates motives related to investment performance, issuers' firm scandals, globalization, environmental changes, shifts in public opinion, and political climate. One effect of the above is that one out of four dollars managed by institutional investors in the USA is invested in Socially Responsible Investment (SRI) funds, while in Europe, it is one out of two dollars [51]. Nowadays, the trend to invest in SRI funds is rising despite evidence indicating they are equal to or less profitable than conventional funds [52–54]. Nevertheless, SRI has less risk, a critical element that would explain the high motivation to invest in this kind of asset [55].

A relevant aspect of ESG assets relates to their response to economic and financial shocks. For instance, there is evidence of additional benefits to the risk–return ratio for SRI funds because SRI funds have lower risk than conventional investments. Ref. [56] shows that SRI funds have a better resilience against shock events by observing that the stability of the structure of the SRI fund network varies less in the face of a highly negative event. Similarly, ref. [57] finds that SRI investments vary less in market fluctuations, while [58] states that SRI investments have lower beta and standard deviation than conventional investments, and refs. [59,60] point out that during times of crisis, SRIs perform better, demonstrating that these funds can protect against periods of turbulence while sacrificing profitability in periods of calm.

Consequently, ESG assets are better prepared to tackle market risks and consider synchronization as an additional market risk, showing better performance during high uncertainty and volatility periods. Regarding this idea, ref. [61] finds that high-ESG funds perform better after crises. Similarly, analyzing stock indices, ref. [62] demonstrates that highly sustainable stock indices can be included in portfolios to increase diversification and risk hedging.

3. Materials and Methods

We used daily closing prices provided by Bloomberg from January 2012 through December 2021 for the 100 largest market cap ETFs worldwide, equivalent to 80% of total assets under management for the ETF industry. Similarly, we obtained the ESG score for each ETF from REFINITIV. Additionally, we included the CBOE VIX index to represent the change in the stock market implied volatility.

Finally, we classified the ETFs around their ESG score in four equally numbered quartiles q. For this purpose, we ordered our 100 ETFs from the highest ESG score ETF to the lowest ESG score ETF, considering the year 2021 score classification. The ESG score is calculated once a year; in this sense, our base premise for this study is that the ESG score ETF is fixed around time.

3.1. Measuring Stock Market Synchronization with MSTL

We compute a minimum spanning tree (MST) to measure synchronization following [34] for each quartile q in the month t. The method is described below. Let N be the number of ETFs and $P_{i,t}$ the price at time t of ETF i, $1 \geq i \geq N$. Then, $r_{i,t}$ the log-return at time t of ETF i, is:

$$r_{i,t} = \log P_{i,t} - \log P_{i,t-1} \tag{1}$$

For each pair i, j of ETFs, we estimate their correlation, using:

$$\rho_{i,j} = \frac{\langle r_i r_j \rangle - \langle r_i \rangle \langle r_j \rangle}{\sqrt{\left(\langle r_i^2 \rangle - \langle r_i \rangle^2\right)\left(\langle r_j^2 \rangle - \langle r_j \rangle^2\right)}} \tag{2}$$

Given a number of N ETFs, there are $N(N-1)/2$ correlations of returns between pairs of ETFs. The $\langle * \rangle$ operator, indicates the average of the quantity on a given month. The ρ_{ij} values of the correlation matrix are transformed to a distance metric, such that $d_{ij} = \left(2\left(1-\rho_{ij}\right)\right)^{1/2}$, which represents the distance between ETF i and j. Thus, a correlation $\rho_{ij} = -1$ indicates a maximum distance of $d_{ij} = 2$, while $\rho_{ij} = 1$ indicates a minimum distance of $d_{ij} = 0$ [37]. The resulting asset distance matrix is part of the input to find a minimum distance asset tree. This tree is a simplified version of the complete correlation network that only has $N-1$ edges as opposed to the original $N(N-1)/2$ edges. This minimum distance tree is equivalent to solving the shortest path problem which can be solved with Kruskal's algorithm [63].

In this way, MST reduces the information by connecting all nodes with $N(N-1)/2$ edges to a tree with $(N-1)$ edges. Then, the sum of the edges of the resulting tree T^t calculated for each month t forms a time series. We define the normalized length of the MST (MSTL) as:

$$L(t) = \left(\frac{1}{N-1}\right) \sum_{d_{ij}^t \in T^t} d_{ij}^t \tag{3}$$

Then, for every month, we estimate the variation in the MSTL as $\Delta L(t) = lnL(t) - lnL\ (t-1)$ for work with a stationary time series.

3.2. Measuring the Shape of the Network

To characterize the minimum distance asset tree obtained in each of the respective time periods, we use graph diameter and degree measure that account for the topological structure of the asset tree.

We define the graph tree as $G = (V, E)$, V and E being the set of vertices and weighted edges of the network, respectively, with adjacency matrix A, then $k_i = \sum_j a_{i,j}$ is the number of edges which are adjacent to the node $v_i \in V$, called the degree of node v_i. All nodes in G, such as $k_i = 1$, are called leaves of the tree. The diameter D of the tree G is defined as the maximum distance between a pair of nodes. It is worth noting that since the set of edges E represents distances, in this case, the diameter of the tree must consider the weights of the edges, which are not the same as the maximum number of edges to connect a pair of nodes. The number of leaves and the diameter are two useful measures to characterize the minimum asset tree. As indicated by [64], trees with a low number of leaves but high diameter usually have a row shape of connected nodes, while trees with a high number of leaves and low diameters usually resemble star-like graphs. In the first case, information can be thought of as flowing through the network in a sequential manner, following a single path, while in the second case, information is concentrated in a few nodes and disseminated to the rest of the network from these high-degree nodes.

Finally, we estimate the strength for each node as a vertex v_i defined as $s_i = \sum_{i \neq j} d_{ij}$, i.e., the sum of the connectivity weights of the edges that connect with node v_i. In our case, a node with a low strength value relative to another indicates that the node is closer to the others or tends to move synchronously with the rest of the nodes to which it is connected. Then, for each month t, we collapse this measure in a mean and a standard deviation within each quartile q.

Our methodology, based on minimum spanning trees (MSTs), is widely validated and extended in financial studies because the network approach in this type of study allows us to consider the multiple interrelationships between actors in a complex system. More specifically, the financial system with N components (indexes or shares of a company) exists for each element with at least $N - 1$ interactions. This method means there are total $N(N-1)/2$ interactions. Consequently, to simplify the network complexity, an MST is used as a filter to reduce the number of connections between the system elements, leaving a graph with only $N - 1$ edges and, simultaneously, leaving the most relevant connections at each node. This approach has been used intensively in other studies, even outside the financial field.

3.3. Econometrics Models and Evaluation

We use the variation of the MSTL, the diameter, and the mean centrality described in the previous section to test the effect of a change in the stock market implied volatility on the ETFs' synchronization. For this aim, we use the t-statistic associated with the coefficient of VIX, considering HAC standard errors as suggested in [65,66]. For covariance stationary processes, the central limit theorem requires a proper estimation of the long-run variance.

Our model specification is the following:

$$VMSTL_{q,t} = \alpha + \beta_q VVIX_t + \sum_{n=1}^{3} \gamma_{t-n} VMSTL_{q,t-n} + e_q \quad (4)$$

where $VMSTL$ is the change in the synchronization of the qth quartile, for all quartiles $q \in \{1, 2, 3, 4\}$ in the month t, and $VVIX$ is the change in the CBOE VIX index in the month t. n represents the number of lags of the $VMSTL$ for each quartile q.

Specifically, we compare the coefficients β_q for each quartile (See Equation (4)) to test the sensibility of synchronization confronting volatility changes. We hypothesize that β_4 (quartile with ETFs with lower ESG scores) is more significant than the β_1 (ETFs with higher ESG scores). This means that, during increased market volatility episodes, correlation networks of ETFs with higher levels of ESG scores present a lower synchronization level compared with correlation networks of ETFs with lower levels of ESG scores.

We apply models using HAC standard errors [65,66] (ref. [65] proposes a Barlett kernel for a positive definite variance matrix, and ref. [66] considers an automatic selection for the lag truncator parameter) because the prices of financial assets are unit root processes since their first difference (log-returns) exhibits covariance stationary.

Considering that we are dealing with time series, the data uncertainty may be manifested not only by the eventual appearance of "rare events" but also by problems of misspecification of such models.

In the first case, there are situations in which an event has high consequences (e.g., an out-of-range return with high consequences or a disproportionately negative return) with little or no historical records available to predict it. Thus, such surprise events could bias our models because they are based primarily on data that are not rare events. However, in our data sample, it is clear that we have some of these rare events that correspond to financial crises that led to market crises and unusual behavior.

In the second case, a miss-specification of our models can occur in the time-series context since we use a finite sample, and consequently, the time series starts from initial conditions. So, we assumed that the process had reached a steady state, so the mean and variance of the dependent variable no longer change over time. This strategy, of course, is a matter of empirical verification that must be carried out because if the process under analysis does not contemplate stationarity, the estimated models will have a bias in parameters and variances because the data are no longer independent. For this case, we have implemented a series of Dickey–Fuller and Phillips–Perron tests of stationarity which indicate that the time series are stationaries (result upon request).

Finally, we added a robustness test using regression with breaks to manage the data uncertainty issues. Given the instabilities in the predictive performance of forecasting models reporting in the literature, we develop a multiple unknown break regression analysis between changes in the VIX and the corresponding variation on the MSTL. The rationale of this exercise is that many papers have data uncertainty problems with sporadic and unstable parameters, appearing as "pockets of predictability" [67]. For this reason, we explore the possibility of multiple unknown breaks in the parameters in Equation (4).

We consider a maximum of five breaks; hence, we allow for a maximum of six different regimes. We determine each regime breakpoint, namely, T1, T2, T3, T4, and T5 using the UDmax test of [68]. Thinking that we have five breaks, we say that the regime 1 is between T0 < T1; regime 2 is between T1 < T2; regime 3 is between T2 < T3; regime 4 is between T3 < T4; regime 5 is between T4 < T5; and regime 6 is between T5 < T6.

3.4. Spillovers Analysis

Following the last stage of our empirical strategy, we study how the mutual interdependence between the VIX and the changes in the MSTL of each ESG network dynamically evolve. For this, we apply an impulse response function exercise and a forecast error variance decomposition [69]. The idea is to gain a broad view of this interconnectedness phenomenon and quantify its mutual influence over time. The IRF function is:

$$\begin{bmatrix} vmstl\_Q1_t \\ vmstl\_Q2_t \\ vmstl\_Q3_t \\ vmstl\_Q4_t \end{bmatrix} = \sum\nolimits_{k=1}^{K} A_k \begin{bmatrix} vmstl\_Q1_{t-k} \\ vmstl\_Q2_{t-k} \\ vmstl\_Q3_{t-k} \\ vmstl\_Q4_{t-k} \end{bmatrix} + B_l * VIX_t + \begin{bmatrix} \varepsilon_{vrmstl\_Q1t} \\ \varepsilon_{vrmstl\_Q2t} \\ \varepsilon_{vrmstl\_Q3t} \\ \varepsilon_{vrmstl\_Q4t} \end{bmatrix} \tag{5}$$

This model captures the length of the synchronization episode, incorporating the response of the variation on the MSTL of each ETF network after a shock of one standard deviation in the VIX.

We are interested in observing the contribution of VIX in the MSTL for each ESG quarter. For this, we developed a simple VAR model by measuring the directional spillovers in a generalized VAR framework. Following [70], we estimate shares of forecast error variation in all quartiles, including VIX due to shock appearance. The intuition behind this is that the forecast error variance of variable i is decomposed into parts attributed to the participation of various variables in the system. For example, we decompose the forecast error variance of VMSTL Q1 into parts attributed to *VMSTL* Q2, *VMSTL* Q3, *VMSTL* Q4, and VIX. We denote by $d_{i,j}^{H}$ the ij–th H-step variance decomposition component; that is, the fraction of variable i' s H-step forecast error variance due to shocks in variable j.

4. Results

4.1. Univariate Results

We use VMSTL to capture the changes in the synchronization within each network according to their ESG score. In this sense, when the network is extending (contracting), the VMSTL is positive (negative), since synchronization within each quartile is diminishing (increasing).

Table 1, Panel A shows a lower synchronization behavior among the ETF quartiles with the highest ESG score (Q3 and Q4) versus the ESG quartiles with the lowest ESG score (Q1 and Q2). The analysis confirms statistically significant differences at 1% between Q3/Q4 compared with Q1/Q2, indicating that the group of ETFs with higher ESG scores has a greater MSTL, consequently exhibiting less synchronization of returns. These MSTL differences are consistent with the diameter measure of each network. As Panel B indicates, the quartiles with the lowest ESG score (Q1 and Q2) present a smaller diameter than the ETFs with the highest ESG score (Q3 and Q4), indicating larger synchronization within the ETFs with the lowest ESG scores.

Table 1. ETFs Network measures by ESG quartiles.

		Q2	**Q3**	**Q4**
			Panel A: MSTL	
Q1	All period	0.939 ***	−0.875 ***	−0.214 **
	2017M01–2018M01	1.176 ***	−1.441 ***	−0.835 ***
	2020M03–2021M03	0.977 ***	−0.509 **	0.271 *
Q2	All period		−1.815 ***	−1.154 ***
	2017M01–2018M01		−2.620 ***	−2.011 ***
	2020M03–2021M03		−1.487 ***	−0.705 ***
Q3	All period			0.661 ***
	2017M01–2018M01			0.608 ***
	2020M03–2021M03			0.781 ***
			Panel B: Diameter	
Q1	All period	0.144 ***	−0.264 ***	−0.023
	2017M01–2018M01	0.093	−0.689 ***	−0.575 **
	2020M03–2021M03	0.449 **	0.147	0.361 **
Q2	All period		−0.408 ***	−0.167 ***
	2017M01–2018M01		−0.783 **	−0.669 **
	2020M03–2021M03		−0.302 **	−0.087
Q3	All period			0.241 ***
	2017M01–2018M01			0.114
	2020M03–2021M03			0.213 *

Table 1. *Cont.*

		Q2	**Q3**	**Q4**
		Panel C: Mean Strength		
Q1	All period	0.039 ***	−0.036 ***	−0.009 ***
	2017M01–2018M01	0.049 ***	−0.060 ***	−0.025 ***
	2020M03–2021M03	0.041 ***	−0.021 **	0.011 *
Q2	All period		−0.075 ***	−0.048 ***
	2017M01–2018M01		−0.109 ***	−0.082 ***
	2020M03–2021M03		−0.061 ***	−0.029 ***
Q3	All period			0.028 ***
	2017M01–2018M01			0.025 ***
	2020M03–2021M03			0.032 ***

Note: ***, **, and * represent statistical significance levels of 1%, 5%, and 10%, respectively. For this analysis, we applied a paired t test for related samples. This table exhibits the mean differences among the row quartiles and the column quartiles. Panel A shows the minimum spanning tree length (MSTL); Panel B shows the diameter; and Panel C shows mean strength. Source: authors' elaboration.

Additionally, to have a sense of the ETF network's shape, we study the strength of each ETF network within its quartile (see Table 1, Panel C). As the literature states, higher (lower) strength networks are associated with star-like (worm-like) shapes. Accordingly, several nodes with high strength act as a source of contagion (hub nodes) rather than receiving the contagion effect from other nodes. From this perspective, a more star-shaped network would transmit a shock faster than a worm-shaped one. As Panel C exhibits, there is evidence of higher strength among the group with higher ESG scores compared with the group with lower ESG scores. These results would indicate that Q3/Q4 tend to be more star-shaped, consequently, they possess a higher risk of contagion than Q1/Q2.

As Figure 1 and Table 1 show, the networks have different topologies during periods of high/low volatility episodes. For instance, tree lengths tend to be greater (smaller) during low (high) volatility periods. In line with previous studies [8,71], the correlation of stocks during financial shock episodes presumably increases due to self-organized crowding behavior [72]. Similarly, from a topological viewpoint, the same is valid for the diameter and mean strength due to the increase in the length of each edge linking the ETFs belonging to each network. Finally, as previous results indicate, the behavior of the different networks is dynamic through time, changing their topological characteristics as stock market conditions vary.

In addition, to appreciate the topology of the ETF networks and illustrate their differences, we built two sets of MST ETF networks for each of the four previous quartiles based on their ESG scores. Figure 1A represents the network structures considering a period of mild uncertainty and volatility (The VIX index for the period January 2013 to April 2021 exhibits a range of variation characterized by a mean equal to 16.87 units, a percentile 25 of 12.71 units, a percentile 50 of 14.52 units, and a percentile 75 of 18.74 units). Similarly, Figure 1B depicts the networks for each quartile considering a period of great uncertainty and volatility when the VIX index had a value of 53.43 units.

Finally, to deepen the understanding of the relationship between volatility and turmoil episodes and their effect on the return's synchronization, particularly on our ETF networks, we first estimate the correlation between each quartile ETF-MSTL (Figure 2). Second, we study the relationship between the VIX and the MSTL-Q1 and MSTL-Q4 (Figure 3).

As both figures display, there is a negative relationship between the four quartiles of ETF and the VIX. In other words, when the VIX rises due to a shock, the MST length belonging to each quartile shrinks. The same occurs to the MSTL grouping the whole sample of ETFs. Moreover, it is possible to appreciate differences in the behavior of the lowest (Q1) vs. highest (Q4) ESG ETFs.

In summary, the univariate analysis lets us conclude that the turmoil episodes captured by changes in the VIX influence the shape and structure of each ETF network and its synchronization level. Likewise, the evidence shows that the topology of each network also changes when the implied volatility of the market varies.

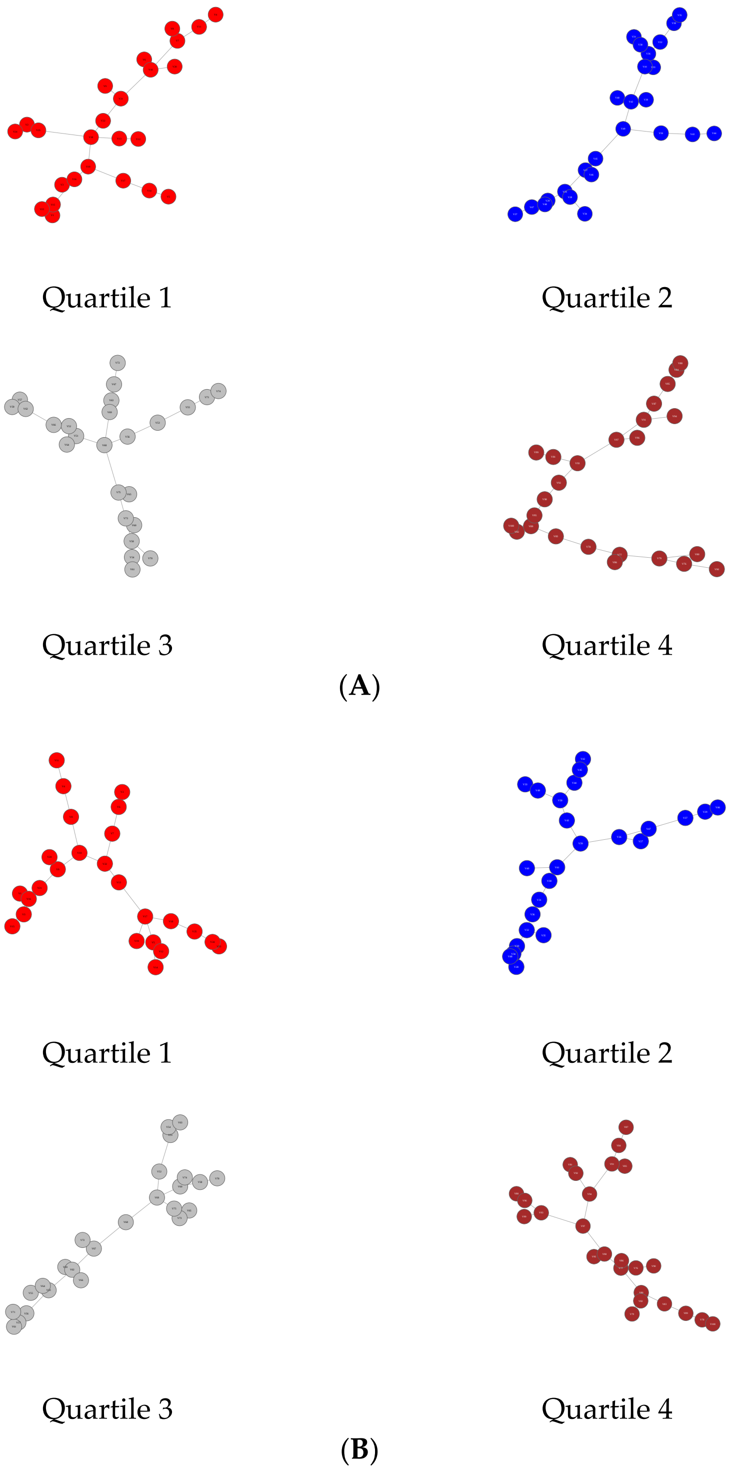

Figure 1. Minimum Spanning Trees (MST) for the ETF industry. This figure shows the resulting MST for two different periods. (**A**) shows a month with higher implied volatility. (**B**) shows a month with lesser implied volatility. We group the ETFs in four quartiles according to their ESG score. Quartile 1 has the lowest ESG score; meanwhile, Quartile 4 has the highest. (**A**) Normal period—October 2017—VIX level: 9.49; (**B**) COVID-19 outbreak period—March 2020—VIX level: 53.43. Source: authors' elaboration.

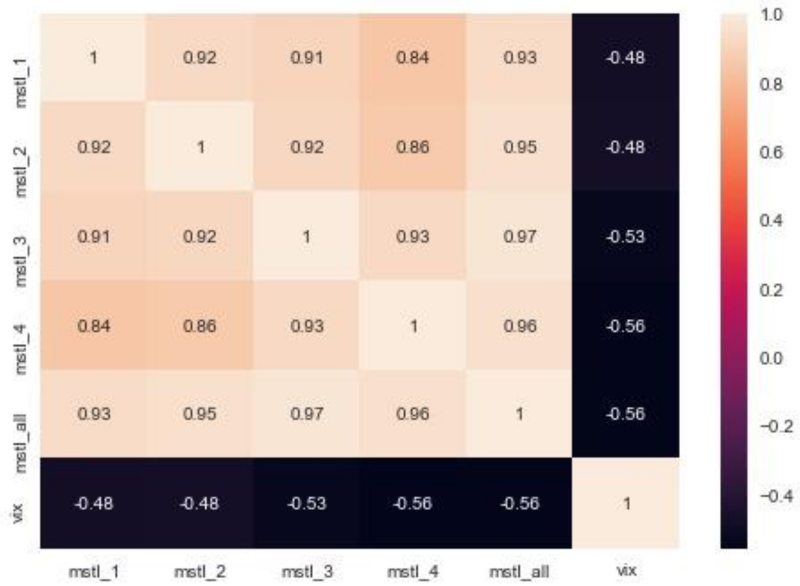

Figure 2. MSTLs and VIX correlation. This figure shows the resulting correlation among each MSTL quartile, the MSTL of all ETFs and the VIX. Source: authors' elaboration.

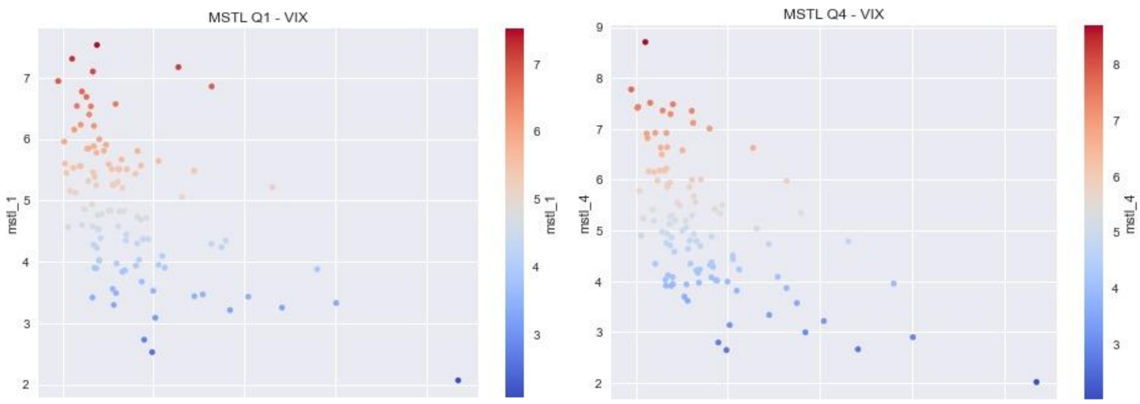

Figure 3. MSTL Q1–MSTL Q4 and VIX. This figure shows the relationship between the VIX and the MSTL-Q1 and MSTL-Q4 for the full period under analysis. Source: authors' elaboration.

4.2. Multivariate Results

In this section, we compare the coefficients β_q for each quartile (See Equation (4)) to test the sensibility of synchronization confronting volatility changes. We hypothesize that the correlations network synchronization in the ETFs quartile with lower ESG scores is more sensible than in the ETFs quartile with higher ESG scores confronting VIX variations. In other words, we are interested in observing that $\beta_1 < \beta_4$. This means that, during increased market volatility episodes, the correlation networks of ETFs with higher levels of ESG score present a lower synchronization level compared with the correlation networks of ETFs with lower levels of ESG score.

Our results are in line with the hypothesis. Table 2, column 1 shows that Q1 (ETFs quartile with lower ESG scores) is the most synchronized during an increase in the VIX compared with the rest of the quartiles. Effectively, at an aggregate level, there is a negative relationship between the VIX and the synchronization of the ETF network (Table 2, column 5). Nevertheless, the reaction for each ETF network is dissimilar. Therefore, the correlations network synchronization in the ETFs quartile with lower ESG scores is more sensible than in the ETFs quartile with higher ESG scores.

Table 2. MSTL and Diameter models.

	Panel A					Panel B				
	(1)	**(2)**	**(3)**	**(4)**	**(5)**	**(6)**	**(7)**	**(8)**	**(9)**	**(10)**
	Q1 (Lowest ESG)	**Q2**	**Q3**	**Q4 (Highest ESG)**	**All Sample**	**Q1 (Lowest ESG)**	**Q2**	**Q3**	**Q4 (Highest ESG)**	**All Sample**
	VMSTL					**DIAMETER**				
VIX	***−0.100 ****	−0.011	−0.011	***0.057 **	***−0.511 ****	***−0.411 ***	−0.068	***−0.269 **	−0.207	***−1.179 ****
	(0.035)	(0.021)	(0.021)	***(0.033)***	***(0.075)***	***(0.163)***	(0.183)	***(0.152)***	(0.157)	***(0.311)***
Z(−1)	***−0.083 ****	***−0.094 ****	***−0.094 ****	−0.041	***−0.431 ****	0.125	−0.062	**0.031**	***0.121 ***	***0.278 ****
	(0.027)	***(0.014)***	***(0.014)***	(0.036)	***(0.065)***	(0.060)	(0.077)	***(0.070)***	***(0.050)***	***(0.100)***
Z(−2)	−0.035	−0.024	−0.024	−0.048	***−0.170 ***	0.039	0.079	***0.099 **	0.094	−0.010
	(0.022)	(0.015)	(0.015)	(0.044)	***(0.069)***	(0.063)	(0.075)	***(0.058)***	(0.058)	(0.089)
Z(−3)	***−0.037 ***	***−0.024 ***	***−0.024 ***	0.001	0.012	***−0.114 ***	−0.082	0.074	−0.029	***0.148 ***
	(0.017)	***(0.010)***	***(0.010)***	(0.029)	(0.070)	***(0.051)***	(0.066)	(0.065)	(0.057)	***(0.070)***
VMSTL_ALL	***0.893 ****	***0.905 ****	***0.905 ****	***1.030 ****						
	(0.033)	***(0.014)***	***(0.014)***	***(0.036)***						
DIAMETER_ALL						***0.471 ****	***0.385 ****	***0.465 ****	***0.563 ****	
						(0.044)	***(0.031)***	***(0.069)***	***(0.079)***	
C	0.001	−0.001	−0.001	0.000	0.000	***0.419 **	***0.930 ****	0.272	−0.320	***2.544 ****
	(0.002)	(0.001)	(0.001)	(0.004)	(0.003)	***(0.249)***	*(0.328)*	(0.223)	(0.300)	***(0.636)***
Adj R^2	0.905	0.913	0.913	0.930	0.375	0.517	0.508	0.576	0.675	0.088
F-stat	198.167	218.753	218.753	278.451	16.575	23.444	22.642	29.485	44.620	3.539
Prob(F-stat)	0.000	0.000	0.000	0.000	0.000	0.000	0.000	0.000	0.000	0.010

Note: Panel A shows the regression for the change in the MSTL (VMSTL_q) for each quartile q using Newey–West standard errors; Panel B shows the regression for the change in the Diameter (Diameter_q) for each quartile q using Newey–West standard errors; VIX is the change in the VIX in the month t; Z is the change in the MSTL (Diameter in Panel B) for each quartile q with one, two, and three lags, respectively; VMSTL_ALL is the change in the MSTL for all sample; DIAMETER_ALL is the change in the diameter for all sample; and standard errors in parentheses. * $p < 0.1$, ** $p < 0.05$, and *** $p < 0.01$. Source: authors' elaboration.

Additionally, the multivariate analysis indicates that the synchronization phenomena throughout the quartiles of ESG ETF networks are not pervasive. Namely, we do not observe the synchronization phenomenon among the quartiles with the higher ESG scores. Moreover, as Table 2, columns 3–4 indicate, the effect of a change in the VIX is not present among the quartiles with higher ESG scores, suggesting that ETFs with a higher ESG level offer a greater synchronization risk protection compared with ETFs with a low ESG score. For instance, results for the Q4 (column 5) network show that a higher VIX provokes a less synchronized network since the network extends. Hence, during periods of financial shocks, both types of ETFs would exhibit different behaviors in terms of their risk synchronization exposure. Consequently, ETFs with lower ESG ratings would be less effective as a diversification tool than those with higher ESG scores.

We complement our study by analyzing the diameter for the whole ETF sample and each quartile. The diameter is representative of how extended or contracted a network is. A network with a smaller diameter is a contracted network, which indicates a more prone network to transmit and spread systemic shocks as synchronization. On the contrary, a higher diameter indicates an extended network, representing a network with lessened conditions for an economic and financial shock to be contagious. Table 2, columns 6–10 show that an increase in the VIX decreases the diameter, with statistical significance, for the case of the network of Q1. This evidence shows that the diameter of the ETF network with lower ESG ratings decreases in the face of an increase in volatility in the stock market.

All in all, we observe that the Q1 correlations network is more sensitive to a volatility increase, showing a more significant risk of contagion concerning the other quartiles.

4.3. Robustness Analysis

Following our empirical strategy, to check that previous evidence is independent of the MSTL method, we apply tests to study the robustness of the results. First, we use the Planar Maximum Filtered Graph (PMFGL) for the ESG ETF fund network instead of MSTL as a synchronization measure (see Table 3, columns 6–10). The PMFG's algorithm admits cycles; therefore, despite being an incomplete network, it contains more information than the MSTL. As Table 3 depicts, our robustness analysis confirms the effect of the implied volatility of the stock market on the whole network of ESG ETF funds. Specifically, and in line with the hypothesis, we observe that lower ESG quartile Q1 scores suffer a significant degree of synchronization compared with those with greater rankings.

Additionally, as equity market regime changes are volatility-dependent [71], we study the effects of changes in the VIX on the shape of ESG ETFs' networks. For this, we use measures regarding the mean centrality of each network. As the literature states, an increase in the average strength of the nodes would indicate that the network takes a star shape, which is associated with a higher risk of contagion since the nodes are more connected on average. On the contrary, a worm shape (less average strength) has a lower risk of contagion. Table 3, columns 1–5 show that an increase in the implied volatility of the stock market negatively affects the mean strength of the ESG ETF funds' global network. Likewise, an increase in the VIX generates a decrease in the mean strength of the ETF subnetwork with the lowest ESG ranking (Q1). Similarly, we also observe that an increase in the mean strength of the whole network of ESG ETF funds generates a rise in the mean strength of the ETF subnetworks.

In summary, our multivariate analysis indicates that changes in the implied volatility of stock markets, represented by the VIX, affect the correlation network structure of the whole ESG ETF funds and their synchronization behavior. Specifically, we find a more negative relationship between the VIX and the synchronization of the Q1 ETF network, the subnetwork of funds with the lower ESG rating. This group synchronizes most under volatility shocks. Concerning the structure of the networks, our evidence indicates that an increment in the implied volatility of the stock market diminishes the diameter and mean strength of the whole network of ETFs, particularly the subnetworks of ETFs with the lowest ESG ratings.

Table 3. Strength and PMFGL models.

	Panel A					Panel B				
	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)	(9)	(10)
	Q1 (Lowest ESG)	Q2	Q3	Q4 (Highest ESG)	All Sample	Q1 (Lowest ESG)	Q2	Q3	Q4 (Highest ESG)	All Sample
	STRENGTH					VPMFGL				
VIX	−0.785 **	−0.086	−0.111	0.375	−18.385 ***	−0.143 ***	−0.042	−0.040	0.051 *	−0.525 ***
	(0.322)	(0.260)	(0.228)	(0.278)	(3.560)	(0.029)	(0.055)	(0.030)	(0.028)	(0.044)
Z(−1)	0.054 *	−0.013	−0.017	0.058	0.406 ***	−0.093 ***	−0.087 ***	−0.068 **	−0.039	−0.425 ***
	(0.027)	(0.038)	(0.023)	(0.037)	(0.091)	(0.023)	(0.022)	(0.031)	(0.042)	(0.039)
Z(−2)	0.006	−0.016	0.038	0.016	0.102	−0.021	−0.010	−0.008	−0.034	−0.178 ***
	(0.019)	(0.029)	(0.027)	(0.030)	(0.072)	(0.025	(0.027)	(0.030)	(0.050)	(0.038)
Z(−3)	0.004	−0.020	0.018	0.067	0.059	−0.033 *	−0.022	−0.011	−0.001	0.014
	(0.022)	(0.031)	(0.025)	(0.020)	(0.089)	(0.019)	(0.019)	(0.030)	(0.029)	(0.038)
STRENGTH_ALL	0.224 ***	0.183 ***	0.218 ***	0.233 ***						
	(0.011)	(0.008)	(0.007)	(0.013)						
VPMFGL_ALL						0.875 ***	0.928 ***	0.954 ***	1.037 ***	
						(0.032)	(0.040)	(0.031)	(0.044)	
C	−0.035	0.719	0.268	−1.589	20.388 ***	0.001	0.000	0.002	0.000	0.000
	(0.667)	(0.468)	(0.549)	(0.620)	(2.680)	(0.003)	(0.002)	(0.003)	(0.004)	(0.002)
Adjusted R-squared	0.916	0.913	0.928	0.894	0.225	0.906	0.916	0.948	0.923	0.376
F-statistic	230.620	222.303	272.771	177.606	8.637	200.814	229.260	380.946	250.408	16.666
Prob(F-statistic)	0.000	0.000	0.000	0.000	0.000	0.000	0.000	0.000	0.000	0.000

Note: Panel A shows the regression for the change in the STRENGTH for each quartile q using Newey–West standard errors; Panel B shows the regression for the change in the PMFGL for each quartile q using Newey–West standard errors; VIX is the change in the VIX in the month t; Z is the change in the STRENGTH (PMFGL in Panel B) for each quartile q with one, two, and three lags, respectively; STRENGTH_ALL is the change in the STRENGTH for all sample; PMFGL_ALL is the change in the PMFGL for all sample; and standard errors in parentheses. * $p < 0.1$, ** $p < 0.05$, and *** $p < 0.01$. Source: authors' elaboration.

4.4. Instabilities and Connectedness Analysis

Table 4, columns 1 to 4 show model estimation results for the analysis of time dependence of parameters considering the four quartiles of ESG ETF networks. We observe that in four of the six regimes, there is a negative relationship between the VIX and the variation of the MSTL, this relationship being concentrated on those networks with less ESG score. However, for the case of the highest ESG network, evidence indicates a positive relationship, suggesting that a rise in VIX tends to expand the Q4 network, favoring a lessened synchronization behavior of the ESG funds within the network.

Table 4. Time dependence of parameters.

	(1)	(2)	(3)	(4)
	Q1 (Lowest ESG)	**Q2**	**Q3**	**Q4 (Highest ESG)**
		VMSTL		
Regime 1				
VIX	***−0.087 ****	0.114	***0.200 ***	−0.013
	(0.017)	(0.118)	***(0.076)***	0.077
Time period (T1)	2013M02–2015M08	2013M02–2015M06	2013M02–2015M05	2013M02–2015M01
Regime 2				
VIX	0.031	***−0.077 ****	0.048	−0.049
	(0.028)	***(0.024)***	(0.039)	0.099
Time period (T2)	2015M09–2016M11	2015M07–2016M11	2015M06–2016M10	2015M02–2016M04
Regime 3				
VIX	***−0.519 ****	***−0.198 **	***−0.156 ****	0.14
	(0.053)	***(0.103)***	***(0.052)***	0.131
Time period (T3)	2016M12–2018M05	2016M12–2018M10	2016M11–2019M01	2016M05–2017M07
Regime 4				
VIX	−0.09	***0.118 **	−0.039	***0.445 ****
	(0.069)	***(0.060)***	(0.056)	***0.081***
Time period (T4)	2018M06–2019M08	2018M11–2021M10	2019M02–2021M10	2017M08–2018M10
Regime 5				
VIX	***−0.142 ****			0.105
	(0.049)			0.093
Time period (T5)	2019M09–2021M10			2018M11–2020M01
Regime 6				
VIX				0.005
				0.039
Time period (T6)				2020M02–2021M10
Adj R^2	0.910	0.927	0.958	0.947
F-statis	37.402	58.621	103.625	54.516
Prob(F-stats)	0.000	0.000	0.000	0.000

Note: This table shows the regressions for the change in the MSTL for each quartile q under different time periods; VIX is the change in the VIX in the month t; regressions included the same variables as Table 2 but does not report; and Newey–West standard errors in parentheses. * $p < 0.1$, ** $p < 0.05$, and *** $p < 0.01$. Source: authors' elaboration.

In summary, these results support the evidence reported in Tables 2 and 3, indicating that our results still show a negative relationship between the VIX and the synchronization of the returns of ESG funds through different time regimes, even incorporating the instability of the parameters observed in the financial markets.

To study the mutual interdependence between the VIX and the changes in the MSTL of each ESG network, we applied an impulse response function exercise and a forecast error variance decomposition. We aim to observe the interconnectedness phenomenon and quantify their mutual influence over time. Figure 4 shows the impulse–response functions for each quartile network. These figures show that the MSTL of each network negatively reacts to VIX innovations, the network with the lowest ESG score, the one that synchronized more.

Finally, Table 5 exhibits the variance decomposition that results from the contribution to the variance of the h-month-ahead synchronization forecast error between each MSTL network and VIX and vice versa. Panel A exhibits 1-month-ahead forecasts error variance decomposition for the MSTL, and Panel B shows the same analysis for the PMFG. On the one hand, we can observe for both synchronization measures that the networks with the lowest (highest) ESG scores contribute more (less) to the rest of the networks in terms of synchronization spillovers and to the VIX. However, on the other hand, the evidence shows that the networks with the highest (lowest) ESG scores receive less (more) synchronization spillovers from the VIX.

Table 5. Mutual spillovers analysis.

Panel A–VMSTL	**Q1**	**Q2**	**Q3**	**Q4**	**VIX**	**From Others**
Q1	25.5	21.9	21.3	19.5	11.8	74.5
Q2	22.0	25.7	22.5	20.1	9.6	74.3
Q3	21.1	22.2	25.3	21.8	9.5	74.7
Q4	20.4	21.0	23.1	26.8	8.7	73.2
VIX	18.2	14.7	14.8	12.8	39.4	60.6
Contribution to others	81.8	79.8	81.7	74.3	39.7	357.3
Contribution including own	107.3	105.5	107.0	101.1	79.1	71.5%
Panel B–VPMFG	**Q1**	**Q2**	**Q3**	**Q4**	**VIX**	**From Others**
Q1	25.3	22.6	21.4	19.7	11.0	74.7
Q2	22.2	25.6	22.2	20.8	9.2	74.4
Q3	21.1	22.1	25.2	22.5	9.1	74.8
Q4	20.2	21.3	22.9	27.4	8.2	72.6
VIX	18.3	15.4	15.5	12.4	38.4	61.6
Contribution to others	81.9	81.4	81.9	75.5	37.4	358.1
Contribution including own	107.2	107.0	107.2	102.9	75.8	71.6%

Note: Panel A summarizes the forecast error variance decomposition results as percentage points among VMSTL of all quartiles and VIX. Panel B summarizes the forecast error variance decomposition results as percentage points among VPMFGL of all quartiles and VIX. The variance decomposition is based on the spillover analysis. Source: authors' elaboration.

As a final remark, it is worth noting that the previous analysis sheds light regarding the synchronization phenomenon regarding ESG ETF and its relationship with financial shocks captured by the VIX. In general, this relationship is negative for the whole network of ESG ETFs, but it is more intense among the ETFs with poorer ESG scores. Additionally, the length of the synchronization episodes tends to be similar for the whole network of funds.

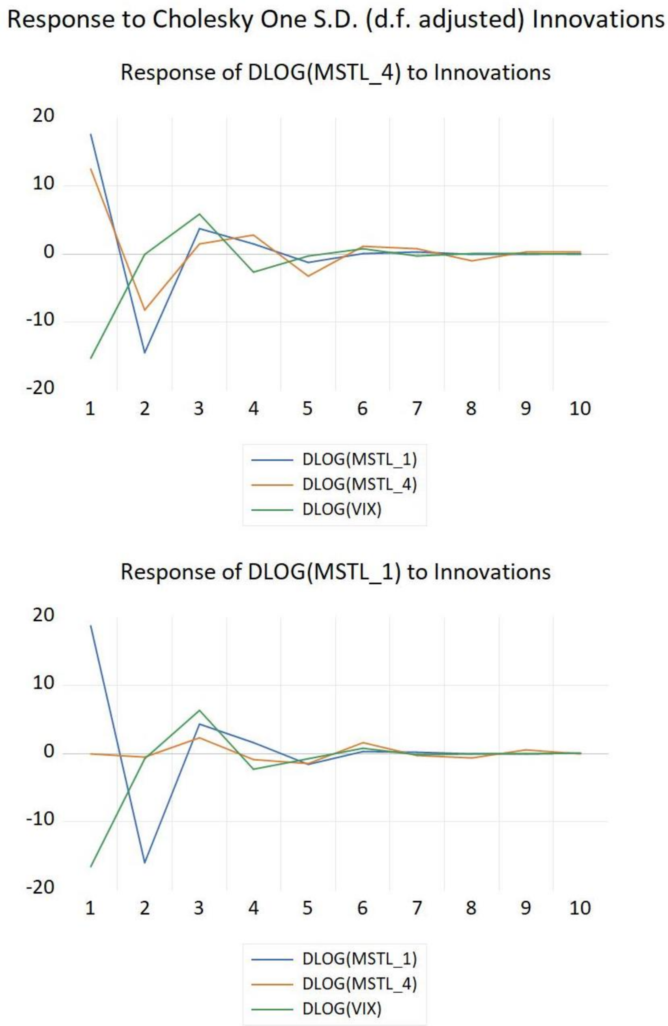

Figure 4. Impulse response function analysis. This figure shows the response to Cholesky One Standard Deviation innovations ± 2 analytic asymptotic Standard Errors to MSTL_Q4 (**up**) and MSTL_Q1 (**down**), respectively. Blue line represents the answer to a MSTL_Q1 innovation. Orange line shows the answer to a MSTL_Q4 innovation. Finally, green line represents the answer to a VIX innovation. Source: authors' elaboration.

5. Discussion

The results show that high ESG ETFs are synchronized less than low ESG ones under rising expected market volatility. This evidence is consistent with the idea that the highest ESG rating mitigates the impact of unexpected change in the implied volatility on the systemic stock market risk.

Our findings align with the financial literature that studies the nexus between ESG score and financial performance, especially with financial risk level (see more details in Appendix B). Using network analysis, ref. [51] compares funds that are highly ranked in ESG aspects with those with poor ESG compliance. They indicate that SRI funds have a better resilience against shocks by observing that the stability of the structure of the SRI fund network varies less in the face of a higher adverse event. Similarly, ref. [60] studies the risk-adjusted financial performance of sustainability funds, finding a better performance than other thematic funds in high volatility periods.

In addition to all this evidence, ref. [59] investigated the performance of SRI funds during crisis, finding that they protect investors from downside risk. Previously, ref. [57] examined stock ESG scores, their returns, volatility, and risk-adjusted returns in the post-2008 financial crisis era. Their results show a negative relationship between ESG and volatility. The authors observed that a high ESG rating and low volatility positively impact stock returns, given the well-documented low-volatility anomaly (outperformance of low-volatility stocks).

We propose that our results could be due to three explanations present in the financial literature. First, investors would adjust their expectations of future cash flows and discount rates to a lesser extent against risks in assets with high ESG. This idea means that investors tend to hold onto high-ESG investments and sell low-ESG ones when faced with increases in market volatility. This behavior occurs because investors believe that assets with high ESG can better confront the risks that underlie an increase in implied volatility, commonly related to economic and financial crises [60]. Consequently, investors facing a shock adjust their expectations of future cash flows and the discount rate on an asset to a lesser extent, with which they tend to maintain their positions over time.

The second explanation is the affect heuristic. Refs. [20,73] indicate that feelings can give way to a more reasoned analysis of decisions and guide subsequent judgment and decision making. Ref. [9] found a strong relationship between the Globe Ranking for the sustainability of mutual funds and expected future returns. A strong negative relationship between the globe's ranking and expected riskiness would suggest a strong role for mutual funds' emotions when managing investments. Along the same lines, this effect is related to the halo effect, where impressions of an area affect the overall evaluation [21]. Thus, the positive evaluation associated with the ESG score of a financial asset could influence a positive evaluation regarding its behavior in difficult times such as financial, economic, or any other shock or crisis that tends to raise the implied volatility of the financial markets.

Finally, a third reason relates to the influence of non-pecuniary motives. In this theory, investors consider environmental and social factors when making investment decisions, making them less reactive to selling high-ESG investments in times of financial instability than low-ESG investments. This phenomenon refers to how other non-economic motivations could influence an investor's self-perception of a financial asset [22,23] and prosocial decision-making processes [24]. For instance, ref. [25] shows that an investor can experience altruism, which in our study can be experiencing satisfaction and well-being when investing in high-ESG ETFs, feeling that they are responsible and benefiting society by selecting high-ESG assets. Additionally, refs. [26,27] point out that these altruistic rationales can come from motives and social pressures, such as the desire to impress others or avoid scorn or negative social reaction.

6. Conclusions

The main result of our article is that there are differences in correlation behavior among ETFs according to their ESG score. Specifically, the high-ESG ETFs quartile is less sensitive to variations in global financial risk than the low-ESG ETFs quartile. In contrast, we find that the synchronization of low-ESG ETFs rises during an increase in the implied volatility of the stock market, while the synchronization of high-ESG ETFs does not react to the same event.

Synchronization in financial assets is a fundamental component of asset pricing theory and the behavior of capital assets. It is particularly relevant in stock markets since shocks and contagion events generate market volatility and stock correlation. The co-movement is a consequence of changes in market information and risk appetite that move the prices together [74].

In the presence of rational investors and a frictionless market, the price of a financial asset would correspond to the rational expectation of its future cash flows, discounted at a rate that adequately reflects the risk associated with those cash flows. Consequently, co-movement in the returns of risky assets, such as stocks of a specific economic sector, would result from the following factors: news correlated with the level of future cash flows or news correlated with the risk of those cash flows. Similarly, it is probable to observe co-movement in returns at the level of all risky assets in the economy due to news regarding future variations in interest rates or changes in investors' overall level of risk aversion [75].

Study synchronization is essential for several reasons: (1) synchronization limits diversification opportunities from the investors' perspective since more synchronized markets and assets imply more extraordinary diversification efforts and costs; (2) from a regulatory perspective, market stability is related to the probability of contagion from economic and financial shocks since a more synchronized market generates the conditions for a shock to be transmitted and spread more quickly; (3) and synchronization is dynamic over time, implying diversification opportunities for investors and policymakers' supervisory task variations.

More importantly, this research shows that ESG ETFs returns' synchronization varies over time, reacting differently to volatility shock according to their ESG ranking. This crucial result suggests new avenues for research that will allow practitioners, investors, and regulators to deepen their understanding of the ESG impact on financial assets. A direct extension would be the construction of indicators to efficiently monitor this new dimension of systemic risk among this broad asset class.

This research has some limitations. First, we eliminate the idiosyncratic equities risk when working with ETFs, so we only focus on market risk and general market factors in our study of synchronization. Second, our network measurements are monthly frequency, which does not allow us to capture the immediate effect of volatility shocks in greater depth on a daily or weekly frequency. Therefore, the generalization of our results should be circumscribed to the behavior of the monthly equity ESG ETF asset class. Third, it is possible that the actual category label associated with ESG assets (because sustainable investments are living a worldwide boom) would change in the future; therefore, the main findings of this work could vary. Finally, from a methodological point of view, a limitation of our study relates to the use of Pearson correlations, which only capture the level of linear association between assets. Thus, the measure of synchronization that the manuscript manifests is a limited feature of the interactive evolution between a pair of elements of a system that may be highly non-linear. However, this limitation does not threaten the study's validity because we still consider the most critical interactions for each ETF. In other words, we consider the other ETFs' influence on each other. Nevertheless, there is certainly an interesting field of exploration where other measures of association consider the non-linearity of the inter-relationships, such as the use of entropy measures.

Our work collects data from REFINITIV as a source for the information collected regarding the ESG scores of the ETFs. Although it is an institution with reliable global coverage in delivering financial information, its experience in ESG aspects is still developing. However, as it is a globally recognized institution in the financial and corporate world and widely used among the leading international investment firms, its use as a data source would allow the replication of these kinds of studies in other markets and countries. It also facilitates improving data collection and reporting systems for the financial market. Likewise, using REFINITIV as a source of ESG information allows different studies to be compared globally. One of the leading global shortcomings associated with ESG information is the lack of comparability between different information providers.

Concerning the generalization of our results, the results may be maintained for the class of assets employed in this study, particularly stock ETFs with a high level of liquidity. However, replicating the results would be a matter of analysis in case of considering another class of illiquid assets, such as small company ETFs or other financial ETFs considering debt instruments, commodities, and cryptocurrencies.

Our study possesses some managerial insights:

1. For investors, to reduce the risk of synchronization in the face of adverse shocks, it is recommended to invest in ETFs with a high ESG score.
2. For regulators to encourage the ESG information to promote a better decision-making process.
3. For investment managers, our evidence illustrates another alternative to managing portfolio risk based on the ESG score of funds.

Regarding future research, we believe this paper opens new perspectives of learning about the advantages of investing in financial assets with a high ESG score beyond its contribution to the environment, society, and governance dimensions. In addition, our results promote the interest in exploring other ways of understanding the contagion phenomenon in financial markets, particularly about ESG assets, such as co-integration, co-movement, connectedness methodologies, and the development of indicators that enhance systemic risk monitoring and promote the ESG factor as a critical financial stability element.

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Appendix A. Comparative Analysis of the Theoretical and Empirical Financial Networks Literature

Main Themes	Authors	Year	Application	Main Results
Stability & fragility of financial systems	Kiyotaki, N.; Moore, J. [28]	1997	Dynamic models of spillovers between lenders and borrowers.	The dynamic interaction between credit limits and asset prices is a powerful transmission mechanism by which the effects of shocks persist, amplify, and spill over to other sectors.
	Allen, F.; Gale, D. [29]	1997	Analysis of the behavior of financial markets when dealing with no diversifiable risks and the presence of intermediaries.	In an economy with intermediaries and no financial markets, accumulating reserves of safe assets allows returns to be smoothed, the non-diversifiable risk to be eliminated, and an ex ante Pareto improvement comparedwith the allocation in the market equilibrium to be achieved.
	D. Acemoglu, A. Ozdaglar, and A. Tahbaz-Salehi [76]	2015	Study of stability and financial contagion among financial networks of interbank liabilities.	A densely connected financial network enhances financial stability. Nevertheless, beyond a certain point, dense interconnections serve as a mechanism for the propagation of shocks, leading to a more fragile financial system. Moreover, the same factors contributing to resilience under certain conditions may function as significant sources of systemic risk under others.

Main Themes	Authors	Year	Application	Main Results
Networks of financial assets	Mantegna, R.N. [34]	1999	Graph analysis of the topological structures of financial stock markets.	There is a hierarchical arrangement of stocks traded in a financial market. The topological space is a subdominant ultrametric space associated with a graph connecting the stocks of the portfolio analyzed. The hierarchical tree of the subdominant ultrametric space associated with the graph provides a meaningful economic taxonomy.
	Mantegna, R.N.; Stanley, H.E.; Chriss, N.A. [37]	2000	Applications to financial markets of power-law distributions, correlations, scaling, unpredictable time series and random processes.	The behavior of complex systems such as financial markets could be explained by applying mathematical and physics techniques.
	Albert, R.; Jeong, H.; Barabási, A.L. [30]	2000	Analysis of the robustness of complex systems under the occurrence of errors.	All redundant systems do not share error tolerance: it is displayed only by a class of non-homogeneously wired networks. Error tolerance depends on selecting and removing a few nodes that play a vital role in maintaining the network's connectivity.
	Bernard, P.; Ahmed, K.; Pierre, C.J.; Nouredine, Z.; Zekri, L. [31]	2008	Study of the propagation of wildfire using small-world models.	Forest fire patterns are fractal, and that critical exponents are universal, which suggests that the propagation/non-propagation transition is a second-order transition. Universality tells us that the characteristic critical behavior of propagation in real systems can be extracted from the simplest network model.
	Haldane, A.G. [32]	2013	Discussion of the behavior under stress of a complex and adaptive network of financial institutions and assets.	Financial markets as a complex adaptive system allow considering some of the lessons from other network disciplines (ecology, epidemiology, biology, and engineering) into the financial sphere. In addition, network approaches provide a different view of the structural vulnerabilities built up in the financial system over the past decade and suggest ways of improving its robustness in the period ahead.
	Nikolaus Hautsch, Julia Schaumburg, Melanie Schienle [77]	2015	Using network interdependence between firms' tail risk exposures to estimate the measure of financial companies' contribution to systemic risk.	Results reveal many relevant risk spillover channels and determine companies' systemic importance in the U.S. financial system. Monitoring companies' systemic importance and enabling transparent macroprudential supervision is crucial for financial stability.

Main Themes	Authors	Year	Application	Main Results
	Haldane, A.G. [32]	2012	Discussion regarding the modeling of risks in financial markets.	Modern finance is complex. Regulation of modern finance is almost certainly too complex. That configuration spells trouble. Because complexity generates uncertainty, not risk, it requires a regulatory response grounded in simplicity, not complexity.
	Eberhard, J., Lavin, J. F., & Montecinos-Pearce, A. [35]	2017	Analysis of the structure of brokers' transaction network of stocks.	Changes in the networks of transactions are correlated with variables that describe economic–financial environments. In addition, changes in the brokers' transaction network structure are associated with a greater probability of positive shocks of more than two standard deviations in the stock exchange index return and total traded stock volume.
	Lavin, J.F.; Valle, M.A.; Magner, N.S. [6]	2019	Study of the topology and connectivity structure of mutual funds and stocks Applying bipartite network methods.	Changes in the bipartite network between stocks and funds and its one-mode projection are correlated with variables related to funds' investment strategies and industry-specific variables. Consequently, these elements are a new source of potential disturbance in the financial network conformed by stocks and mutual funds.
	Lavin, J.F.; Valle, M.A.; Magner, N.S. [8]	2021	Modeling synchronization in stock markets using correlation-based network methods.	Global stock synchronization is dynamic over time, its minimums coincide with significant financial shocks, and it shrinks to its minimum levels, indicating that the returns of global markets are moving in a synchronized way. Moreover, it is a significant and positive factor in regional synchronization. Regional markets react heterogeneously to global synchronization shocks, suggesting that local and global factors are synchronization sources.
Portfolio selection & risk management	Onnela, J.P.; Chakraborti, A.; Kaski, K.; Kertész, J.; Kanto, A. [36]	2003	Applying asset trees to reflect the economic taxonomy of stock correlations and portfolio diversification.	The diversification dimension of portfolio optimization results in the fact that the assets of the classic Markowitz portfolio are located on the outer leaves of the asset tree formed by the stocks (nodes) and their respective distances (correlations).
	Diebold, F. & Yılmaz, K. [70]	2014	Using variance decomposition estimations as natural and insightful measures of connectedness among financial firms.	Variance decompositions define weighted, directed networks so that connectedness measures are intimately related to key measures of connectedness used in the network literature.

Main Themes	Authors	Year	Application	Main Results
	Výrost, T., Lyócsa, Š., & Baumöhl, E. [40]	2019	Analysis of portfolio optimization techniques based on network-based models and centrality measures of stocks.1	Network-based asset allocation strategies improve key portfolio return characteristics in an out-of-sample framework, most notably, risk and left-tail risk-adjusted returns. Resolving portfolio model selection uncertainties further improves risk–return characteristics
Integration of financial markets & Forecasting models	Q. Ji, E. Bouri, and D. Roubaud [78]	2019	Analysis of information flow among U.S. equities, strategic commodities (oil and gold), and BRICS equities using dynamic networks models.	The integration structure of an information transmission network is unstable and changes over time. The impact patterns of events are dissimilar—some events impact the local market only, whereas others have a global impact.
	Gao, H. L., & Mei, D.C. [38]	2019	Study of the dynamics of correlation structures between U.S. and Asian stock markets.	Non-linear effects dominate stronger dependencies between all indices after the 2008 financial crisis. The synchronicity decreases for significant variations of firm specifics. The 2008 global financial crisis spread rapidly to Asian markets compared with several other financial crises or crashes. China's stock and U.S. markets exhibit a lack of interdependence during the 2008 financial crisis.
	Magner, N.S., Lavin, J.F., Valle, M.A., Hardy, N. [39]	2020	Applying network-based models to forecasting the implied volatility of stock markets.	The length of the minimum spanning tree is relevant to forecast volatility in European and Asian stock markets, improving forecasting models' performance. In addition, the evidence from this work establishes a road map to deepen the understanding of how financial networks can improve the quality of prediction of financial variables. The latter is crucial during financial shocks, where uncertainty and volatility skyrocket.
	Magner N, Lavin JF, Valle M, Hardy N. [74]	2021	Analysis of the use of the implied stock market's volatility indices' predictive power on synchronizing global equity indices returns.	An increase in the markets' volatility expectations, captured by the implied volatility indices, is a good Granger predictor of an increase in the synchronization of stock market returns in the following month.

Appendix B. Comparative Analysis of Theoretical and Empirical Financial Performance and the ESG Literature

Main Themes	Authors	Year	Application	Main Results
Neutral impacts of ESG on financial performance	Bauer, R., Koedijk, K., & Otten, R. [54]	2015	Study the effect of ESG level on mutual funds returns	Mutual funds with high ESG levels have no better performance than lower-ESG-level mutual funds.
	Mill G. [53]	2006	Examines the financial performance of a UK unit trust that was initially "conventional" and later adopted socially responsible investment (SRI) principles (ethical investment principles).	Mean risk-adjusted performance is unchanged by the switch to SRI, with no evidence of over-or under-performance relative to the benchmark market index by any of the four funds.
	Hamilton, Sally, Hoje Jo, and Meir Statman. [79]	1993	Compare the mutual funds' financial performance between socially responsible and conventional mutual funds	Socially responsible mutual funds do not earn statistically significant excess returns, and the performance of such mutual funds is not statistically different from the performance of conventional mutual funds.
	Statman, M., & Glushkov, D. [80]	2009	Study the stock returns of companies with high scores on social responsibility characteristics and shun stocks of companies associated with tobacco, alcohol, gambling, firearms, and military or nuclear operations.	Authors find evidence consistent with the "no effect" hypothesis, whereby the expected returns of socially responsible stocks are approximately equal to the expected returns of conventional stocks.
	Aw, E. N. W., LaPerla, S. J., & Sivin, G. Y. [81]	2017	Study portfolios that outperform a benchmark while allowing investors to embrace ESG.	Top-quintile (most compliant) stocks ranked by ESG score underperform the out-sample research universe.

Main Themes	Authors	Year	Application	Main Results
Positive impacts of ESG on financial performance	Statman, Meir. [82]	2000	Using an index of socially responsibility named "Domini Social Index" to compare the financial performance of the SRI and conventional mutual funds.	The Domini Social Index performed better than the S&P 500 Index, but the differences between their risk-adjusted returns are not statistically significant.
	Serafeim, G. [83]	2020	Study the "public sentiment influences investor views" about the value of company sustainability activities.	The valuation premium for strong sustainability performance increases as a function of positive momentum in public sentiment. An ESG factor long (short) on companies with superior (inferior) sustainability performance and negative (positive) ESG sentiment momentum delivered significant positive alpha.
	Konar, S., & Cohen, M. A. [84]	2001	Study the market value of firms in the S&P 500 to objective measures of their environmental performance.	[84] Ad environmental performance is negatively correlated with the intangible asset value of firms. Specifically, a 10% reduction in emissions of toxic chemicals results in a USD 34 million increase in market value (this magnitude varies across industries).
	Durán-Santomil, P., Otero-González, L., Correia-Domingues, R. H., & Reboredo, J. C. [85]	2019	Study the effects of socially responsible investments (SRI) on European equity fund performance.	Sustainability scores impacted positively on financial performance considering returns and risk.
	de Franco, C. [86]	2020	Study USA, Asia-Pacific, and Europe portfolios based on this measure of controversy from environmental, social and governance (ESG) data.	Portfolios that excluded highly controversial stocks outperform their benchmarks, except for the Asia-Pacific zone.
	Bauer, R., Koedijk, K., & Otten, R. [54]	2005	Using German, UK, and U.S. ethical mutual funds the study and explore their financial risk.	Ethical funds are typically less exposed to market return variability; they are small and more growth-oriented compared with conventional funds.

Main Themes	Authors	Year	Application	Main Results
Impact of ESG on financial risk	De, I., & Clayman, M. R. [57]	2015	Examine the relationship between the ESG ratings of a company and its stock returns, volatility, and risk-adjusted returns in the post-2008 financial crisis era.	There is a negative relationship between ESG and volatility in greater depth, given the well-documented low-volatility anomaly (outperformance of low-volatility stocks). Both (high) ESG rating and (low) volatility positively impact stock returns, but the ESG effect is independent of the low-volatility effect.
	Nofsinger, J., & Varma, A. [59]	2014	Investigate the performance of SRI funds during crisis and non-crisis periods to empirically test the hypothesis that SRI funds dampen downside risk for investors during poor economic conditions	Compared with conventional mutual funds, socially responsible mutual funds outperform during market crises.
	Becchetti, L., Ciciretti, R., & Hasan, I. [61]	2015	Investigate the nexus between idiosyncratic volatility and corporate social responsibility.	Idiosyncratic volatility (IV) is negatively correlated with corporate social responsibility (CSR-specific stakeholder risk factor).
	Boitan, I. A. [62]	2020	Study the synchronization between the price return provided by sustainability indices calculated for various geographic regions.	Sustainability indices, which include companies from Europe, Japan, U.S., World developed countries, and World best-in-class, exhibit more correlation price returns than conventional assets.
	Ielasi, F., & Rossolini, M. [60]	2019	Compare the risk-adjusted performance of sustainability-themed funds with other categories of mutual funds	Sustainable funds are better than other thematic funds in overcoming financially turbulent periods and currently benefit from SRI regulation and disclosure.
	Cerqueti, R., Ciciretti, R., Dalò, A., & Nicolosi, M. [58]	2020	Compare funds highly ranked in Environmental Social and Governance (ESG) aspects with those with a poor ESG compliance using network analysis.	SRI funds have a better resilience against shock events by observing that the stability of the structure of the SRI fund network varies less in the face of a highly negative event
	Renneboog, L., ter Horst, J., & Zhang, C. [87]	2011	Study the money flows into and out of socially responsible investment (SRI) funds around the world.	SRI money flows are less related to past fund returns. Ethical money is less sensitive to past negative returns than are conventional fund flows, especially when SRI funds primarily use negative or Sin/Ethical screens

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