The Dynamic Volatility Connectedness of Major Environmental, Social, and Governance (ESG) Stock Indices: Evidence Based on DCC-GARCH Model

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Abstract
This study investigates the dynamic volatility connectivity of important environmental, social, and governance (ESG) stock indexes from May 2010 to March 2021. The empirical research is focused on five major S&P ESG stock indexes from the US, Latin America, Europe, the Middle East and Africa, and Asia Pacific regions. The study reveals that ESG stock indexes in the Middle East Africa, and Latin America are net shock transmitters, whereas the United States and Asia Pacific are net volatility receivers. Furthermore, the study finds that bilateral intercorrelations are higher among US, Latin America, and Europe region group pairs and weaker in relation to Middle East Africa and Asia Pacific region group pairs, indicating the presence of contagion within developed and/or emerging regions, which has relevance for portfolio and risk management.

Keywords ESG stock indices · DCC-GARCH · Volatility connectedness · Spillover · VAR

JEL Classification G10 · G15 · E50 · C13

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1 Introduction

A rising number of organizations are seeking ESG accreditations in order to provide supportability evidence and demonstrate their influence on sustainable growth and commitment to the UN Sustainable Development Goals (SDGs). Of late, it is evident that businesses have expanded their contemplation beyond gain, and now the debate over "sustainable reporting" has narrowed from value innovation for the business enterprise to "enterprise value conception" (Van der Waal & Thijsens, 2020). It is presently more vital than ever for businesses to step up their endeavors to incorporate sustainable development principles into their strategy, management approach, and administration oversight, and to be responsible for them. Since 2020 globally as indicated by the Global Sustainable Investment Alliance (GSIA) that Global Sustainable Investment has assets under management of $35.3 trillion, demonstrating the continued popularity of sustainable investment.

Sustainable investment empowers investors to effectively look for investments that might bring significant social or ecological advantages. Additionally, it will doubtlessly accomplish long term returns because of the decrease in likely potential risks (Revelli & Viviani, 2015). During the early 2000s, the fast spread of SRI practices in the world economies prompted research into the growth and evolution of SRI. Before the 1990s, it was common practice in US and in UK to exclude specific stocks from investing portfolios based on nonfinancial reasons. Sustainability indexes are commendable in accomplishing environment/green objectives nonetheless are providing enlargement openings in portfolios of conventional resources and supporting against worldwide instability (Jin et al., 2020).

The rapid development of ESG theme has sparked interest from both investment professionals and academics, this study takes motivation from the ongoing research initiatives that explores ESG indices and comprehend how they vary from the conventional indices. Numerous studies have been conducted on the theme of investment contagion and connectivity and how volatility spreads and contagions across conventional assets like stocks, commodities, currencies among others (Akhtaruzzaman & Shamsuddin, 2016; Liew et al., 2022; Malik & Umar, 2019; Singh et al., 2021; Tiwari et al., 2018; Umar et al., 2019; Yang et al., 2021). But there is there is paucity of research investigations on ESG connectedness.

In order to assess the effects of dynamic volatility connectedness of major Environmental, Social, and Governance (ESG) Stock Indices, our study cover all the regional ESG indices which comprises both developed and emerging market regions of Americas, Europe, the Middle East, and Africa (EMEA), and Asia–Pacific (APAC). The motivation of examining the selected data set for this study is on account of the fact that it is on regional basis and the specified indexes are major ESG markets in terms of depth and breadth and reflect a significant share of the global ESG market capitalization (S&P Global ESG, 2022). In multiple ways, the current study adds to previous literature. First, it adds to the rising literature on how the dynamic volatility connectivity exist in the important environmental, social, and governance (ESG) stock indexes. Second, we add depth by analyzing connectedness patterns in ESG equity indexes among leading
regional ESG markets from 2010 to 2021. Third, we employ a novel technique proposed by Gabauer (2021), in which they utilize a DCC-GARCH (Engle, 2002) model to provide an alternative to the volatility transmission mechanism predicted by Diebold and Yilmaz (2014)’s dynamic connectedness approach without employing a rolling-window framework. The shortcomings of prior versions of the rolling-window technique used to evaluate dynamic volatility connectivity, such as window size and loss of data, are no longer present in this new approach.

Our empirical results reveal some intriguing findings. To begin, this study incorporates regional ESG data, which includes five key S&P ESG stock indexes from the United States, Latin America, Europe, the Middle East and Africa, and Asia Pacific regions, considering the extension of ESG stock indexes and globalization of financial market. The study unearths that ESG stock indexes in the Middle East, Africa, and Latin America are net shock transmitters, whilst the US and Asia Pacific are net volatility recipients.

Our investigation decomposes the risk contagion levels of the ESG stock indices and conducts a quantifiable analysis of the dynamic contagion features across international ESG financial markets. Likewise, pairwise joint effect is stronger in the United States, Latin America, and Europe region group pairings than in the Middle East, Africa, and Asia Pacific region group pairs, confirming the occurrence of transmission within developed and/or emerging regions.

The study makes deep examination of the risk contagion in the selected ESG markets, we propose that the findings, shall offer recommendations for investors to make investment choices on the landscape of ESG stock indices. In investigating the shock transmission among ESG equity indices, our findings have central policy suggestions for global investors, portfolio managers, and governments. Policymakers must assess not only the total connection of financial assets, but also the directional spillover between them. The study covers averaged dynamic connectedness measures, namely, dynamic total connectedness, net directional connectedness, net pairwise directional connectedness. Policymakers can plan opportune arrangement intercessions to moderate spillover chance from the connectedness among ESG equity indices. It is vital for international investors, portfolio investors, governments, and other market partakers to effectively implement risk-mitigation techniques throughout the crisis. As a result, the spillover level and the presence of contagion within ESG stock market indices covering developed and/or emerging regions are explored in this study, which have significance for portfolio and risk management.

The rest of this paper is systematized as follows. Section 2 discusses the literature, while Sect. 3 discusses the methodologies. Section 4 contains a data description and presents the empirical discussions and Sect. 6 concludes.

2 Literature Review

Multiple investigations have revealed that companies with robust ESG scores have higher risk-adjusted returns (Sherwood & Pollard, 2018; Verheyden et al., 2016). The ESG factor has turned into a significant thought for undertakings businesses, asset managers, and other stakeholders. Henke (2016) found that the amazing
superior accomplishment of socially responsible bond funds is linked to the lessening of ESG risks, especially amid downturns or bear markets. Higher ESG activity diminishes total and idiosyncratic risk (Sassen et al., 2016) and lessening downside risk (Giese et al., 2019). A significant part of the ESG investigations has centered on its impact on firm accomplishment (Aouadi & Marsat, 2018).

Further investigation of the volatility risk associated with ESG-based portfolios are conducted. When it comes to volatility risk, Kumar et al. (2016) examine businesses that are part of the Dow Jones Sustainability Index and found that ESG companies exhibit less volatility in their stock performances than their rivals in the identical market. In comparison to the set of equities that are not screened, Verheyden et al., (2016) demonstrate that volatility is lower when ESG filtering is conducted. Hoepner et al. (2011) highlight that high ESG-rated enterprises displayed statistically significant lower worst-case loss, volatility, and other downside associated risk. The study by Akhtaruzzaman et al. (2021) found that US market is a volatility receiver.

A comprehensive study of MSCI ESG index data by Giese et al., (2019) reveals that risk is lessened for ESG-based portfolios. In their investigation of how the stock market responds to news about environmental, social, and governance issues, Capelle-Blancard and Petit (2019) report that businesses that experience adverse events have a 0.1% loss in market value while firms that yield good announcements on average do not show any gains. In their examination into how ESG factors effect stock returns, La Torre et al. (2020) concluded that ESG strategies had a beneficial impact on returns for a small number of companies, primarily in niche areas like energy and utilities.

ESG factors, based on various studies, can enhance portfolio risk and return. In fact, Shanaev and Ghimire (2022) discover evidence demonstrating that ESG enhancements boost abnormal returns and vice versa. Based on the most thorough meta-study of more than 1,000 articles published between 2015 and 2020 (Whelan et al., 2021), 58% of those publications uncover a positive link between ESG and financial success, while only 8% demonstrate a negative relationship. The other 34% of those studies discover neutral or mixed results. One the one side, various studies with an emphasis on the GFC era uncover evidence to back up the premise that ESG acts as a downside risk mitigator. (Lins et al., 2017; Nofsinger & Varma, 2014). Additionally, there is indication that ESG serves as a robustness component in the face of uncertainty in a slew of recent studies that emphasize on the COVID-19 period (Broadstock et al., 2021; Diaz et al., 2021).

Wu et al. (2022), examined the effect of ESG certification on the pricing efficiency. They find that stocks with ESG lists have better pricing efficiency performance. Pavlova and de Boyrie (2021) investigated risk-adjusted returns on 62 funds before and after the current pandemic crisis utilizing Morningstar data. They report higher appraisals did not safeguard the funds from misfortunes amid the downturn 2020, in any case they did not deliver more regrettable compared to the rest of the members.

Ferriani and Natoli (2021) revealed that, low-risk ESG funds observed optimistic investment inflows amid and after the stock market bust, though significant-risk ESG witnessed sell-offs amid the freeze stage and a while later. Whereas high-risk
ESG funds saw sell-offs during the bust phase and afterwards. While all of the funds studied had adverse cumulative returns, low-risk funds fared much superior than the rest. Singh (2020) through MSCI data gauged finds that risk averse investors sought refuge in CSR portfolios during the May 2017–May 2020. Broadstock et al. (2021) investigate the part of ESG performance in China prior to and during the pandemic, discovering that portfolios with a high ESG score outperform portfolios with a low ESG score. They revealed that high environmental, social, and governance (ESG) performance reduces risk during the pandemic. Equities with robust ESG ratings are more robust during times of crisis, according to Albuquerque et al. (2020). Stocks with high ESG ratings had altogether more noteworthy returns, lower return unpredictability and more trading volumes than other stocks. (Climent and Soriano, 2011) employed a CAPM-based approach and revealed that within the 1987–2009 period, environmental funds underachieved conventional funds with comparable attributes.

The dynamic connectedness procedure based on vector auto regressions proposed by the works of Diebold and Yilmaz () has fascinated momentous attention in the economics and finance literature (Antonakakis et al., 2018). Umar et al., (2021) used the spillover index approach of Diebold and Yilmaz (2012) to investigate the risk spillover relationship among the ESG markets of ten major countries. They revealed ESG markets has noteworthy time-varying features, and the ESG market in developed nations is the primary source of risk spillover in worldwide markets. The recent health pandemic, COVID-19 has impacted the global economy across all asset classes (Salisu and Shaik, 2022; Singh et al., 2021). The study by Umar et al., (2021) use a time frequency investigation to understand the influence of COVID-19 induced panic on the precariousness of ESG indices.

There is little research on dynamic volatility connectivity between S&P ESG from advanced and emerging equity markets regional indices. This gap in the literature is filled by our research where we apply the latest DCC GARCH based volatility connectedness approach put forth by Gabauer, 2021 on ESG stock indices. In line, our study covers the regional ESG indices and the specified indexes are major ESG markets in terms of depth and breadth and reflect a significant share of the global ESG market. We utilize the S&P ESG, as a proxy for ESG investments. The momentous development of ESG investment opportunities around the world propels us to examine dynamic connectedness measures between ESG indices.

3 Data Description

We use daily data of five major S&P’s environmental, social, and governance (ESG) stock market indices of U.S (ESG_US), Latin America (ESG_LA), Europe (ESG_EUR), Middle East Africa (ESG_MEA), and Asia Pacific (ESG_AP) for period from April 30th, 2010 to March 3rd, 2021. The starting point (30-04-2010) is chosen based on the availability of the data for all the indices under consideration. The daily price series data is downloaded from the source Bloomberg. We first convert the non-stationary price series to return series computed as
\[
\log \left( \frac{P_t}{P_{t-1}} \right), \text{ to make the series stationary.}
\]

Figures 1 and 2 display the plots of the five major ESG stock index prices and return series respectively.

Table 1 shows the descriptive statistics of the returns. The number of daily observations of the stock indices returns are 2728. The highest mean return (0.043) is observed for the U.S stock index and the lowest mean return (−0.023) is observed for Latin American index. We observe Latin American index to have the highest variance (3.104) and the Asia Pacific stock index to have the lowest variance (1.039). We observe all the stock indices to have negative skewness, high kurtosis values and
are not normally distributed as per the Jarque Bera (JB) test. The return series are observed to be stationary in nature as per ERS unit root test (Stock et al., 1996). Furthermore, we observe that the return series exhibit ARCH errors based on weighted portmanteau test (Q2(10)). Since we observe ARCH errors, it becomes appropriate to estimate multivariate GARCH procedure.

### 4 Methodology

#### 4.1 DCC-GARCH Model

Engle’s (2002) two-step DCC-GARCH model is used to investigate dynamic conditional volatility. The DCC-GARCH(1,1) model is expressed as follows:

\[
y_t = \mu_t + \epsilon_t \quad \epsilon_t | F_{t-1} \sim N(0, H_t)
\]

\[
\epsilon = H_t^{1/2} u_t \quad u_t \sim N(0, I)
\]

\[
H_t = D_t R_t D_t
\]

where \( F_{t-1} \) denotes all available information up to \( t - 1 \). \( y_t, \mu_t, \epsilon_t, \) and \( u_t \) are \( N \times 1 \) dimensional vectors indicating the investigated time series, conditional mean, error term, and standardised error term, respectively. Furthermore, \( R_t, H_t, \) and \( D_t = diag \left( h_{11}^{1/2}, \ldots, h_{NN}^{1/2} \right) \) are \( N \times N \) dimensional matrices that represent dynamic conditional correlations, time-varying conditional variance–covariance matrices, and time-varying conditional variances.

In the first stage, \( D_t \) is measured by calculating a Bollerslev (1986) GARCH model for every sample. According to Hansen and Lunde (2005)’s research, one shock and one persistency parameter are assumed.
The dynamic conditional correlations are calculated in the second step as follows:

\[ h_{ii,t} = \omega + a\varepsilon_{i,t-1}^2 + \beta h_{ii,t-1} \]  

(4)

where \( Q_t \) and \( \overline{Q} \) are \( N \times N \) dimensional positive-definite matrices representing the variance–covariance matrices of conditional and unconditional standardised residuals, respectively. \( a(\alpha) \) and \( b(\beta) \) are non-negative shock and persistency parameters that meet the equation, \( a + b < 1 (\alpha + \beta \leq 1) \). As long as \( a + b < 1 \) is satisfied, \( Q_t \) and hence \( R_t \) change over time; otherwise, this model converges to the CCC-GARCH model, in which \( R_t \) is constant over time.

4.2 Dynamic Connectedness Approach

It’s worth noting that the connectedness model developed by Diebold and Yilmaz () is based on the generalised impulse response functions (GIRFs) proposed by Koop et al. (1996) and Pesaran and Shin (1998). The benefit of GIRFs is that they are not affected by the order of the variables and may be understood as the J-step forward impact of a shock in variable \( i \) on variable \( j \). Similarly, the volatility impulse response function (VIRF) depicts the influence of a shock in variable \( i \) on the conditional volatilities of variable \( j \), which may be represented as:

\[ \psi^g = VIRF(J, \delta_{j,t}, F_{t-1}) = E(H_{i+j}|e_{j,t} = \delta_{j,t}, F_{t-1}) - E(H_{i+j}|e_{j,t} = 0, F_{t-1}) \]  

(7)

where \( \delta_{j,t} \) is a selection vector with a one at the \( j \)th point and a zero otherwise. The DCC-GARCH model (Engle & Sheppard, 2001) is used to forecast conditional variance-covariances, which is at the core of the VIRF.

The generalised forecast error variance decomposition (GFEVD) is calculated based on the VIRF and may be understood as the variance share one variable explains on others. These variance shares are normalised such that each row amounts to one, indicating that all variables explain 100% of variable \( i \)’s prediction error variance. This is considered in the following manner:

\[ \bar{\phi}^g_{ij,t}(J) = \frac{\sum_{t=1}^{J-1} \psi^g_{ij,t}}{\sum_{j=1}^{N} \sum_{t=1}^{J-1} \psi^g_{ij,t}} \]  

(8)

where \( \sum_{j=1}^{N} \bar{\phi}^g_{ij,j}(J) = 1 \) and \( \sum_{i,j=1}^{N} \bar{\phi}^g_{ij,j}(J) = N \). The numerator indicates the cumulative effect of the \( i \)th shock, whereas the denominator signifies the aggregate cumulative effect of all shocks. Using the GFEVD, the total connectedness index (TCI) may be calculated as follows:
The Dynamic Volatility Connectedness of Major Environmental,…

Following that, the spillovers variable \( i \) transfers to variables \( j \), which are referred to as total directional connectedness TO others, are figured as follows:

\[
C_{i \rightarrow j, t}^g(J) = \frac{\sum_{j=1, i \neq j}^{N} \tilde{\phi}_{ij, t}^g(J)}{\sum_{j=1}^{N} \tilde{\phi}_{ji, t}^g(J)}
\] (10)

In the following phase, the spillovers variable \( i \) gets from variables \( j \), known as total directional connectedness FROM others, are determined as follows:

\[
C_{i \leftarrow j, t}^g(J) = \frac{\sum_{j=1, i \neq j}^{N} \tilde{\phi}_{ji, t}^g(J)}{\sum_{j=1}^{N} \tilde{\phi}_{ij, t}^g(J)}
\] (11)

Subtracting the two previously mentioned measures yields the net total directional connectedness, which may be read as the effect variable \( i \) has on the examined network:

\[
C_{i, t}^g(J) = C_{i \rightarrow j, t}^g(J) - C_{i \leftarrow j, t}^g(J)
\] (12)

If variable \( i \)'s net total directional connectedness is positive (negative), it signifies that variable \( i \) is a net shock transmitter (receiver) or that variable \( i \) is driving (being driven by) the network.

Finally, the net pairwise directional connectedness (NPDC) between variables \( i \) and \( j \) is calculated as:

\[
NPDC_{ij}(J) = \tilde{\phi}_{ji, t}^g(J) - \tilde{\phi}_{ij, t}^g(J)
\] (13)

where variable \( i \) dominates (is dominated by) variable \( j \), as shown by a positive (negative) \( NPDC_{ij} \).

5 Empirical Results

5.1 Dynamic Connectedness Table

The averaged dynamic connectedness measures are shown in Table 2. The static TCI is equivalent to 54.39%, showing that the ESG stock market indices is strongly linked. Through the table, it is revealed that the Middle East Africa ESG stock index (ESG MEA) is the dominant net transmitter, as it is the main net transmitter to all four ESG stock indexes, followed by the Latin American (ESG LA) index. The ESG index of the United States (ESG US), on the other hand, is the largest net recipient, receiving from all others, second by the ESG index of Asia Pacific (ESG AP).
5.2 Dynamic Total Connectedness

Figure 3 displays the dynamic TCI, which ranges between 50 and 65% and also the adjusted TCI (Chatziantoniou & Gabauer, 2021; Gabauer, 2021) that ranges between 60 and 80%. This practically implies that connectedness across the major five ESG Stock indexes are robust and time-varying is often overlooked by the TCI’s static structure. To be more specific, three spikes can be seen in Fig. 3, the first of which may be linked to the events like UN Sustainable Development Goals, panama papers leakage, landmark paris agreement (2015–2016) and the second to the events like EU’s Sustainable Finance HLEG recommendations (2018), and lastly due to health pandemic COVID-19.

| ESG_US | ESG_LA | ESG_EUR | ESG_MEA | ESG_AP | Contribution FROM others |
|--------|--------|---------|---------|--------|-------------------------|
| 30.16  | 28.51  | 18.19   | 19.01   | 4.13   | 69.84                   |
| 4.81   | 57.90  | 9.93    | 23.00   | 4.35   | 42.10                   |
| 6.32   | 19.93  | 34.15   | 33.26   | 6.34   | 65.85                   |
| 2.33   | 16.40  | 11.55   | 63.56   | 6.17   | 36.44                   |
| 2.39   | 14.93  | 10.30   | 30.11   | 42.28  | 57.72                   |
| Contribution to others | 15.84 | 79.77  | 49.97   | 105.38 | 20.99  | 271.95 |
| NET directional connectedness | – 54.00 | 37.67  | – 15.88 | 68.94  | – 36.73 | TCI         |
| NPDC transmitter | 4 | 1 | 2 | 0 | 3 | 54.39 |

Values reported are variance decompositions based on 100-day ahead forecasts. NPDC represents Net Pairwise Directional Connectedness measures.
5.3 Net Directional Connectedness Measures

It can be observed from panel (i) of Fig. 4, that ESG_MEA (Middle East & Africa) is the net transmitter to all other ESG indices followed by ESG_LA, ESG_EUR, ESG_AP, and then ESG_US. From panel (ii) of Fig. 4, we can find that ESG_US is the net receiver from all other ESG stock indices followed by ESG_AP, ESG_EUR, ESG_LA, and lastly ESG_MEA. Panel (iii) of Fig. 4 depicts the dynamic net total directional connectedness measures of ESG stock indices. Clearly, ESG_US, ESG_AP has been a net receivers thoughout the period, except for a few positive spikes and it can be associated to events like Global initiative for Sustainable Ratings
Montreal Carbon Pledge (2014), EU’s Sustainable Finance HLEG recommendations (2018), and COVID-19 (2020) pandemic. In case of ESG_EUR, it has been a net transmitter until 2012, and then became a net receiver through out the rest of the period, except during 2015 where it became a high net transmitter temporarily and it might be due to the events like landmark Paris agreement which reached at UN COP 21 with an aim to reduce the risks and effects of climate change through universal agreement to reduce carbon emissions, and also introduction of a new compass for sustainable investments and actions through UN Sustainable Development Goals. ESG_LA, and ESG_MEA remained to be net transmitters throughout except for a few negative spikes which might be due to events like global initiative for sustainable ratings (2011), EU’s sustainable finance recommendations (2018), and COVID-19 pandemic (2020).

Furthermore, Fig. 5 supports all previous findings. The pairwise directional connected between ESG_US and the other indices is mostly negative and it can be seen clearly that the bilateral relationship between ESG_US and ESG_AP is weak throughout the period. Similarly, the bilateral relationship is weak between ESG_EUR and ESG_AP, except for a positive spike during 2015 due to events like UN SDGs, Paris agreement on climate change. The bilateral intercorrelations are observed to be higher among ESG_US, ESG_LA, ESG_EUR group pairs and weaker in relation with ESG_MEA or ESG_AP. Further the bilateral relationship is strong among ESG_MEA and ESG_AP indicating the presence of contagion within developed and/or emerging regions which has potential portfolio and risk management implications.
6 Conclusion

With the development and advancement of the worldwide green monetary framework, stakeholders are becoming keener about the ESG stock market. Few researchers have examined into the risk contagion within international ESG stock markets. Our research can help many practitioners in their assessment and decision-making processes by providing insights into the SRI portfolio decision making. Therefore, the current study employed the S&P ESG selected indexes and utilized the DCC-GARCH Model to compute the risk spillovers of the selected ESG stock indexes. In line, the risk spillover and risk contagion mechanism of the selected ESG stock indices were examined.

This study incorporates regional ESG data, which includes five key S&P ESG stock indexes from the United States, Latin America, Europe, the Middle East and Africa, and Asia Pacific regions, considering the extension of ESG stock indexes and globalization of financial market.

The Total connectedness index (TCI) constitutes 54.39 percent, demonstrating that ESG stock market indices are closely connected. Our investigation reveals that ESG stock indexes in the Middle East, Africa, and Latin America constitute net shock transmitters, whilst the US and Asia Pacific represent net volatility recipients.

Our investigation analyses the ESG market’s risk contagion levels and undertakes a quantitative analysis of dynamic transmission elements among international ESG financial markets. Moreover, bilateral intercorrelations are greater in the United States, Latin America, and Europe region group combination than in the Middle East, Africa, and Asia Pacific region group pairs, demonstrating the existence of transmission within established and/or emerging economies.

The research has potential portfolio and risk management implications. The investors and portfolio managers must analyze their exposures ESG stock indexes in order to optimize their asset allocation and risk mitigation measures. Industry and regulators can also improve market volume management and provide a number of ESG market countermeasures. They may be sufficient to thwart the adverse implications of extreme economic events on worldwide ESG markets.

Further research can be conducted in understanding the connectedness of the individual countries within the specific regions and highlight the major individual contributors for the volatility transmissions. Also, we can extend the research by applying advanced methodologies putforth by Batten et al. (2022), Bhatia et al. (2018), Antonakakis et al. (2020), Chatziantoniou et al. (2022) for more robustness of the findings.

References

Akhtaruzzaman, M., Abdel-Qader, W., Hammami, H., & Shams, S. (2021). Is China a source of financial contagion? Finance Research Letters, 38, 101393.

Akhtaruzzaman, M., & Shamsuddin, A. (2016). International contagion through financial versus non-financial firms. Economic Modelling, 59, 143–163.
Albuquerque, R. A., Koskinen, Y., Yang, S., & Zhang, C. (2020). *Love in the time of COVID-19: The resiliency of environmental and social stocks*. CEPR Discussion Papers 14661, C.E.P.R. Discussion Papers.

Anscombe, F. J., & Glynn, W. J. (1983). Distribution of the kurtosis statistic for normal samples. *Biometrika*, 70(1), 227–234.

Antonakakis, N., Chatziantoniou, I., & Gabauer, D. (2018). European currency co-movements and contagion: Evidence from a bayesian TVP-(Pseudo)FAVAR model. *SSRN Electronic Journal*. https://doi.org/10.2139/ssrn.3167203.

Antonakakis, N., Chatziantoniou, I., & Gabauer, D. (2020). Refined measures of dynamic connectedness based on time-varying parameter vector autoregressions. *Journal of Risk and Financial Management*, 13(4), 84.

Aouadi, A., & Marsat, S. (2018). Do ESG controversies matter for firm value? Evidence from international data. *Journal of Business Ethics*, 151(4), 1027–1047.

Ashwin Kumar, N. C., Smith, C., Badis, L., Wang, N., Ambrosy, P., & Tavares, R. (2016). ESG factors and risk-adjusted performance: A new quantitative model. *Journal of Sustainable Finance & Investment*, 6(4), 292–300.

Batten, J. A., Choudhury, T., Kinateder, H., & Wagner, N. F. (2022). Volatility impacts on the European banking sector: GFC and COVID-19. *Annals of Operations Research*. https://doi.org/10.1007/s10479-022-04523-8.

Bhatia, V., Das, D., Tiwari, A. K., Shabbaz, M., & Hasim, H. M. (2018). Do precious metal spot prices influence each other? Evidence from a nonparametric causality-in-quantiles approach. *Resources Policy*, 55, 244–252.

Bollerslev, T. (1986). Generalized autoregressive conditional heteroskedasticity. *Journal of Econometrics*, 31(3), 307–327.

Broadstock, D. C., Chan, K., Cheng, L. T., & Wang, X. (2021). The role of ESG performance during times of financial crisis: Evidence from COVID-19 in China. *Finance Research Letters*, 38, 101716.

Capelle-Blancard, G., & Petit, A. (2019). Every little helps? ESG news and stock market reaction. *Journal of Business Ethics*, 157(2), 543–565.

Chatziantoniou, I., Abakah, E. J. A., Gabauer, D., & Tiwari, A. K. (2022). Quantile time–frequency price connectedness between green bond, green equity, sustainable investments and clean energy markets. *Journal of Cleaner Production*, 361, 132088.

Chatziantoniou, I., & Gabauer, D. (2021). EMU risk-synchronisation and financial fragility through the prism of dynamic connectedness. *Quarterly Review of Economics and Finance*, 79(1), 1–14.

Climent, F., & Soriano, P. (2011). Green and good? The investment performance of US environmental mutual funds. *Journal of Business Ethics*, 103, 275–287. https://doi.org/10.1007/s10551-011-0865-2.

D’Agostino, R. B. (1970). Transformation to normality of the null distribution of g1. *Biometrika*, 57, 679–681.

De Souza Cunha, F. A. F., & Samanez, C. P. (2013). Performance analysis of sustainable investments in the Brazilian stock market: A study about the corporate sustainability index (ISE). *Journal of Business Ethics*, 117(1), 19–36.

Díaz, V., Ibrushi, D., & Zhao, J. (2021). Reconsidering systematic factors during the COVID-19 pandemic—The rising importance of ESG. *Finance Research Letters*, 38, 101870.

Diebold, F. X., & Yılmaz, K. (2009). Measuring financial asset return and volatility spillovers, with application to global equity markets. *The Economic Journal*, 119(534), 158–171.

Diebold, F. X., & Yılmaz, K. (2012). Better to give than to receive: predictive directional measurement of volatility spillovers. *International Journal of Forecasting*, 28(1), 57–66.

Diebold, F. X., & Yılmaz, K. (2014). On the network topology of variance decompositions: Measuring the connectedness of financial firms. *Journal of Econometrics*, 182(1), 119–134.

Engle, R. F., & Sheppard, K. (2001). Theoretical and empirical properties of dynamic conditional correlation multivariate GARCH. Technical report, National Bureau of Economic Research.

Engle, R. (2002). Dynamic conditional correlation: A simple class of multivariate generalized autoregressive conditional heteroskedasticity models. *Journal of Business & Economic Statistics*, 20(3), 339–350.

ESG index family. S&P Global. (n.d.). Retrieved September 15, 2022, from https://www.spglobal.com/esg/performance/indices/esg-index-family#objective.
The Dynamic Volatility Connectedness of Major Environmental,…”

Faroq, U., Nasir, A., Bilal, & Quddoos, M. U. (2021). The impact of COVID-19 pandemic on abnormal returns of insurance firms: a cross-country evidence. *Applied Economics, 53*(31), 3658–3678.

Ferriani, F., & Natoli, F. (2021). ESG risks in times of Covid-19. *Applied Economics Letters, 28*(18), 1537–1541.

Gabauer, D. (2021). Dynamic measures of asymmetric and pairwise spillovers within an optimal currency area: Evidence from the ERM I system. *Journal of Multinational Financial Management, 60*(1), 1000680.

Giese, G., Lee, L. E., Melas, D., Nagy, Z., & Nishikawa, L. (2019). Foundations of ESG investing: How ESG affects equity valuation, risk, and performance. *The Journal of Portfolio Management, 45*(5), 69–83.

Hansen, P. R., & Lunde, A. (2005). A forecast comparison of volatility models: Does anything beat a GARCH (1, 1)? *Journal of Applied Econometrics, 20*(7), 873–889.

Henke, H. M. (2016). The effect of social screening on bond mutual fund performance. *Journal of Banking & Finance, 67*, 69–84.

Hoepner, A. G., Rezec, M., & Siegl, S. (2011). Does pension funds’ fiduciary duty prohibit the integration of any ESG criteria in investment processes? *A realistic prudent investment test. SSRN eLibrary*.

Jarque, C. M., & Bera, A. K. (1980). Efficient tests for normality, homoscedasticity and serial independence of regression residuals. *Economics Letters, 6*(3), 255–259.

Jin, J., Han, L., Wu, L., & Zeng, H. (2020). The hedging effect of green bonds on carbon market risk. *International Review of Financial Analysis, 71*, 101509.

Koop, G., Pesaran, M. H., & Potter, S. M. (1996). Impulse response analysis in nonlinear multivariate models. *Journal of Economics, 74*(1), 119–147.

La Torre, M., Mango, F., Cafaro, A., & Leo, S. (2020). Does the ESG index affect stock return? Evidence from the eurostoxx50. *Sustainability, 12*(16), 6387.

Lins, K. V., Servaes, H., & Tamayo, A. (2017). Social capital, trust, and firm performance: The value of corporate social responsibility during the financial crisis. *The Journal of Finance, 72*(4), 1785–1824.

Malik, F., & Umar, Z. (2019). Dynamic connectedness of oil price shocks and exchange rates. *Energy Economics, 84*, 104501.

Nofsinger, J., & Varma, A. (2014). Socially responsible funds and market crises. *Journal of Banking & Finance, 48*, 180–193.

Pástor, L., & Vorsatz, M. B. (2020). Mutual fund performance and flows during the COVID-19 crisis. *The Review of Asset Pricing Studies, 10*(4), 791–833.

Pavlova, I., & de Boyrie, M. E. (2021). ESG ETFs and the COVID-19 stock market crash of 2020: Did clean funds fare better? *Finance Research Letters, 44*, 102051.

Pesaran, H. H., & Shin, Y. (1998). Generalized impulse response analysis in linear multivariate models. *Economics Letters, 58*(1), 17–29.

Revelli, C., & Viviani, J. L. (2015). Financial performance of socially responsible investing (SRI): What have we learned? A meta-analysis. *Business Ethics: A European Review, 24*(2), 158–185.

Salisu, A. A., & Shaik, M. (2022). Islamic stock indices and COVID-19 pandemic. *International Review of Economics and Finance, 80*, 282–293.

Sassen, R., Hinze, A. K., & Hardeck, I. (2016). Impact of ESG factors on firm risk in Europe. *Journal of Business Economics, 86*(8), 867–904.

Shanaev, S., & Ghimire, B. (2022). When ESG meets AAA: The effect of ESG rating changes on stock returns. *Finance Research Letters, 46*, 102302.

Sherwood, M. W., & Pollard, J. L. (2018). The risk-adjusted return potential of integrating ESG strategies into emerging market equities. *Journal of Sustainable Finance & Investment, 8*(1), 26–44.

Singh, D., Theivanayaki, M., & Ganeshwari, M. (2021). Examining volatility spillover between foreign exchange markets and stock markets of countries such as BRICS countries. *Global Business Review*. https://doi.org/10.1177/09721509211020543.

Singh, A. (2020). COVID-19 and safer investment bets. *Finance Research Letters, 36*, 101729.

Singh, G., & Shaik, M. (2021). The short-term impact of COVID-19 on global stock market indices. *Contemporary Economics, 15*(1), 1–19.

Stock, J., Elliott, G., & Rothenberg, T. (1996). Efficient tests for an autoregressive unit root. *Econometrica, 64*(4), 813–836.
Tiwari, A. K., Cunado, J., Gupta, R., & Wohar, M. E. (2018). Volatility spillovers across global asset classes: Evidence from time and frequency domains. *The Quarterly Review of Economics and Finance, 70*, 194–202.

Umar, Z., Gubareva, M., Tran, K. D., & Teplova, T. (2021). Impact of COVID-19 induced panic on the environmental, social and governance leaders equity volatility: A time frequency analysis. *Research in International Business and Finance, 58*, 101493.

Umar, Z., Nasreen, S., Solarin, S. A., & Tiwari, A. K. (2019). Exploring the time and frequency domain connectedness of oil prices and metal prices. *Resources Policy, 64*, 101516.

Umar, Z., & Suleman, T. (2017). Asymmetric return and volatility transmission in conventional and Islamic equities. *Risks, 5*(2), 22.

United Nations. (2015). *Addis Ababa action agenda*. UN.

Van der Waal, J. W., & Thijsens, T. (2020). Corporate involvement in sustainable development goals: Exploring the territory. *Journal of Cleaner Production, 252*, 119625.

Verheyden, T., Eccles, R. G., & Feiner, A. (2016). ESG for all? The impact of ESG screening on return, risk, and diversification. *Journal of Applied Corporate Finance, 28*(2), 47–55.

Wang, Q., Dou, J., & Jia, S. (2016). A meta-analytic review of corporate social responsibility and corporate financial performance: The moderating effect of contextual factors. *Business & Society, 55*(8), 1083–1121.

Whelan, T., Atz, U., Van Holt, T., & Clark, C. (2021). *ESG and financial performance: Uncovering the relationship by aggregating evidence from 1,000 plus studies published between 2015–2020*. NYU STERN Center for Sustainable Business.

Wu, C., Xiong, X., & Gao, Y. (2022). Does ESG certification improve price efficiency in the Chinese stock market? *Asia-Pacific Financial Markets, 29*, 97–122.

Yang, J., Li, Z., & Miao, H. (2021). Volatility spillovers in commodity futures markets: A network approach. *Journal of Futures Markets, 41*(12), 1959–1987.

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