

The connectedness of financial risk and green financial instruments: a dynamic and frequency analysis

Ngoepe, Letlhogonolo Kearabilwe and Bonga-Bonga, Lumengo

2024

Online at https://mpra.ub.uni-muenchen.de/121091/ MPRA Paper No. 121091, posted 28 May 2024 06:58 UTC

The connectedness of financial risk and green financial instruments: A dynamic and frequency analysis.

Letlhogonolo Kearabilwe Ngoepe Lumengo Bonga-Bonga

Abstract

Various 'green' investment channels cater specifically to environmentally conscious investments. In this paper, we investigate the optimal green investment strategy by comparing the risk of three green financial instruments- green bonds, green equity, and a balanced 50/50 bond equity fund. Using the dynamic and frequency connectedness approaches by Diebold and Yilmaz (2012) and Baruník and Křehlík (2018), we analyze how financial risk affects green investment over various time horizons. Our findings show that green equity possesses the highest risk spillovers. Furthermore, green bonds and the ESG equity index provide risk diversification benefits for green investors. The balanced index displays a low risk-return nexus, further indicating that green investors are better off by investing in a diversified portfolio. Lastly, under unfavourable market conditions, the green investment market instruments provide little to no diversification against each other.

1. Introduction

In recent years, the global conversation surrounding climate change and environmental sustainability has reached a critical point. With increasing awareness of the urgent need to address these challenges, individuals and organizations are seeking ways to contribute positively to the planet's well-being. The 2015 Paris Agreement, or Paris Accords, aimed to embolden climate change efforts by encouraging governments to pledge to the United Nations to provide financing targeting specifically to minimise the impact of climate change. Hence, obtaining green finance has become of increasing concern for investors and policymakers alike.

In response to the growing conversation surrounding climate change, there has been an emergence of various 'green' investment channels that cater specifically to environmentally conscious investments. Green investing, also known as sustainable investing or socially responsible investing (SRI), resulted in a conscious effort to align financial decisions with environmental, social, and governance (ESG) considerations. As a result, investors went beyond conventional investment approaches that are just concerned with maximizing financial gains and acknowledge the significance of funding businesses and projects that place a high value on sustainability and a cleaner, greener future.

Despite there being an increase in the desire for a more environmentally friendly society, green investing is not without challenges. For instance, green investors may become exposed to 'greenwashing', which refers to the practice of misleadingly promoting investments or companies as environmentally friendly when they do not truly meet sustainable criteria. It can be challenging for investors to differentiate between genuinely green investments and those that merely claim to be sustainable. Thorough due diligence and understanding the underlying practices and impacts of investments are essential to avoid falling victim to greenwashing. Furthermore, the green investment market is relatively new and rapidly evolving. Compared to their conventional counterparts, there is limited information on the financial benefits of green financial instruments. Thus, many investors may lack awareness or understanding of sustainable investment opportunities and strategies.

Despite these obstacles, green investing is still on the rise as more investors understand the benefit of solving environmental problems and the possibility of long-term value creation through sustainable practices. However, the financial benefits of green investing are still unclear. It is argued that, since governments aim to increase private funding using green investment, they should provide tax benefits and improved ESG ratings to investors and issuers

(Cicchiello et al., 2022; Teti et al., 2022). Thus, it is of particular interest to investors to identify how they can achieve responsible investment while maintaining high returns and minimising risk.

Over the last decade, many studies have emerged analysing the financial characteristics of green investments. Several studies demonstrated that green bonds displayed greater yields, lower variation, and higher liquidity, and were, therefore, less risky than traditional bonds (Febi et al., 2018; Bachelet et al., 2019). Tan et al. (2022) acknowledge that, due to the long-term nature of the projects that they are funding, green bonds tend to have longer cycles and higher fund demands, as opposed to conventional financial instruments.

An increasing number of studies focus on how green bonds and green equity fare as compared to their conventional counterparts (Chen & Zhao, 2021; Naeem et al., 2021; Tan et al., 2022; Hu et al., 2023). However, very few studies are conducted on the risk-return nexus of green investments, Hu et al. (2023) argue since green bonds are used for acquiring funds for environmental projects, some studies argue that environmental policy uncertainty is an additional risk factor in the analysis of green instruments (Hu et al., 2023). Further, to better understand the risk profile of green finance, studies acknowledge the importance of analysing the connectedness between the green market and other conventional financial instruments (Reboredo, J. C., & Ugolini, 2020; Fernandes et al., 2022; Mensi et al., 2022; Mzoughi et al., 2022; Doğan et al., 2023; Tiwari et al., 2023; Umar et al., 2023). This is mainly due to the overlapping fundamental factors that drive these instruments. However, there are very few studies that are interesting in comparing various green investments and how they compare to each other.

The purpose of this study is to examine the relationship between financial risk and green investments. In doing so, we aim to provide further insights into the existing literature surrounding green investments in various ways. Firstly, we aim to investigate which green financial investment - between green bonds, green equity, and a balanced, equally-weighted fund consisting of green bonds and green equity - is affected the least by financial risk. Through this, we investigate the potential for diversification when investing in green investments of various kinds, Secondly, we employ the dynamic and frequency connectedness model by Diebold and Yilmaz (2012, 2014) and Baruník and Křehlík (2018), in which we analyse the nexus between global risk and green investments. These approaches quantify the spillover between variables using the generalized forecasted error variance decomposition of a vector

autoregressive (VAR) model. By quantifying how the directional spillovers between the variables change over various frequency bands, we can pinpoint the precise time horizons that are primarily attributable to the connection between the variables. We will use the CBOE Volatility Index VIX as a measure of global financial risk.

We undertake this study taking into account two important aspects. Firstly, we assume the perspective of a rational investor. We assume that the rational investor is interested in maximising profits while minimising their risk exposure. Thus, green investors are challenged with balancing the trade-off that may occur between investing responsibly and maximising profits (Gilchrist et al., 2021). Consequentially, although responsible investing may be the investors' objective, they will still choose to engage in the profit-maximising, risk-minimising strategy. Secondly, since a rational investor is concerned with minimising risk, we view the lack of connectedness of variables as a good investment strategy, as it provides diversification of risk.

The remaining sections of the paper are organized as follows. In Section 2, we examine the prior research on the connection between the green financial markets and conventional market segments. This analysis is the basis for the methodological approach, which will be discussed further in Section 3. In Section 4, the empirical findings of our research will be presented and discussed. Lastly, Section 5 will discuss the policy implications of our findings and provide concluding remarks.

2. Literature

Since the first issuance in 2007, numerous studies have surfaced recently that concentrate on the financial characteristics of green investments, for example Cicchiello et al. (2022). According to earlier research, there exists a yield differenctial between green products and conventional financial products with similar features (Zerbib, 2016; Febi et al., 2018; Bachelet et al., 2019). Zerbib (2016), who found that green bonds typically yield between 1 and 9 basis points less than their conventional counterparts, argues that environmental preferences and other non-pecuniary motives of green bond investors contribute greatly to this yield disparity. On the other hand, Zerbib (2019) discovers that despite the existence of these preferences, they have a negligible effect on the cost of green bonds. Prices are more affected by the bond's rating and the issuer's characteristics.

The uncertainty surrounding the underlying characteristics that account for the presence of green premium in the market prompted researchers to better understand the green financial

market. Thus, several studies investigate the interconnectedness between the conventional asset market and the green bond market. Many studies do so by analysing the correlation and comovement of both market assets. Reboredo (2018) finds that green bonds and conventional bond markets display significant co-movement due to their substantial symmetric tail dependence. Furthermore, Reboredo and Ugolini (2020) discover close link between the green bonds and the traditional bonds and currency markets, and a contrastingly tenuous connection to the stock, energy, and high-yield corporate bond markets. Martiradonna et al. (2023) extend the co-movement analysis by designing portfolios based on a range of allocation strategies, those that include green bonds and those that do not, to evaluate how green bond indices affect otherwise conventional portfolios. Using both the Bloomberg Barclays MSCI Green Bond Index and the Solactive Green Bond Index, the study discovers lower risk outcomes in portfolios that include both green bond investments. The diversification provided by SOLGB, however, is greater than that provided by BBGB. Furthermore, strategies that placed a higher priority on reducing variance gave the Bloomberg Barclays MSCI Green Bond Index more weight, while those that focused maximizing diversity only used the Solactive Green Bond Index.

In addition to the co-movement framework, other researchers use spillover models to look examine the interconnectedness green bonds are to other markets. When comparing green bonds to traditional asset classes, these studies show varying degrees of interconnectedness and investing success. Gao and Wang (2021) utilised a the spillover index approach, as well as a multidimensional DCC-GJRGARCH model and to compare the green bond and traditional fixed income markets in China. The study discovered large two-way risk spillovers markets. However, when comparing to other markets, there were minimal risk transfers across the green bond, currency, and money markets. Additionally, market circumstances and unanticipated events were identified as the main causes of spillovers across all markets. Mzoughi et al. (2022) investigate the risk transfers between green financial instruments and the energy commodities market index after applying copulas theory to analyse the dependence structure. Marginal equities exhibit a long memory volatility process, depicted by the estimation of a FIGARCH model. The study concludes that during crucial times, considerable price spillovers from the energy commodities market have a significant impact on green instruments, particularly green bonds.

Furthermore, some literature highlights the need to utilise a dynamic framework that takes into account the possibility of time series dependency. Thus, a growing body of literature provides

time-varying, or dynamic, methodologies to investigate the green bond market. Hammoudeh et al. (2020) utilise a time-varying Granger causality model to determine the connectedness of green bond to other financial instruments, namely US treasury bonds, CO2 emission allowances, and the WilderHill Clean Energy Equity Index, from 2014 to 2020. The results show that green bonds and the US 10-year Treasury bond index had a significant causal association that started at the end of 2016 and persisted through the end of the study period. However, there is no proof of a connection between the other parameters and the green bonds index.

Using a variety of time-independent and dynamic copula approaches, Liu et al. (2021) analyze the dependence between green bonds and a number of clean energy markets from July 2011 to February 2020. The study demonstrates that the GB and CE stock markets exhibit positive time-varying average and tail dependency. Furthermore, it was discovered that major fluctuations in either direction on the price index of the CE stock market had an effect on the GB market, and vice versa. In a further analysis of risk spillovers, by employing conditional and delta value-at-risk (CoVaR), asymetric spillover of risk between the two markets are discovered. In another time-variant study, Nguyen et al. (2021) investigate green bonds' connectedness to stocks, commodities, renewable energy, and classic bonds markets between 2008 and 2019. The dynamic properties of correlation across asset pairs across time and at different frequencies are assessed using the rolling window wavelet correlation approach. The study discovered correlation with the bonds and energy markets, the highest correlation existing in the GFC period; between 2007 and 2009. However, it was found that the link between green bonds and equities and commodities was either extremely low or negative. Green bonds, thus, offered major benefits for diversification in balanced portfolios.

To ascertain the cross-quantile reliance between green bonds and other American and European asset markets, Pham and Nguyen (2021) use a cross-quantilogram technique. The results illustrate quantile spillovers, demonstrating the advantages of utilizing green bonds as a hedge against conventional asset classes. This, however, notably differ depending on whether market conditions are extreme or typical. Additionally, Pham (2021) uses a cross-quantilogram and frequency connectivity technique to examine the green bonds-green equity relationship. The reliance between green bond and green equity under typical market conditions is quite modest, even after accounting for changes in the broader stock, energy, and fixed-income markets. On the other hand, green bonds and green equity are more tightly linked during periods of high market instability, when they boom and collapse jointly. Lastly, the study highlights how the

spillover effects between green bond and green equity become sporadic across all market conditions as the degree of connectedness reduces over the course of medium- and long-term investment periods. In another study, Doğan et al. (2023) postulate the 'safe haven' quality of green bonds. The study uses a number of dynamic models, including cross-quantilogram analysis, quantile coherency estimates, and Granger causality in quantiles. The results indicate that, during crisis times, there is a rise in volatility diffusion from the oil to the green bond markets.

Primarily, the above literature is concerned with how green investments display connectedness to conventional market instruments. However, little attention is paid to the connectedness of instruments within the green market. In other words, there is an opportunity to establish which green financial instrument provides the best financial incentive to its investors.

Thus, as with Pham (2021), we aim to investigate the connectedness between risk green investments. In doing so, we will establish if these investments provide any diversification opportunities. In order to investigate these above objectives, we will adopt the frequency connectedness approach postulated by Diebold and Yilmaz (2012). In our analysis, we will estimate the connectedness between the global volatility and the prices and returns of green bonds, green equity, and a balanced fund. Furthermore, according to our knowledge, no studies have been conducted that compare the risk profile of green instruments and those of a diversified strategy. Thus, we introduce the diversified green investment strategy in which there is a 50/50 allocation to green bonds and green equity. This strategy will be referred to in the paper as 'the balanced fund'.

3. Methodology

3.1.Data

The aim of this study is to investigate the connectedness of the green financial market and overall financial risk. To do so, we utilise daily time series data that reflects the prices of green market instruments– namely green bonds, green equity and a balanced green fund – from 30 April 2013 to 30 November 2022. The S&P Green Bond Index is used to measure the performance of the green bond market and the S&P 500 ESG Index to measure the performance of the green equity market. The S&P 500 ESG Index is a widely based, market capitalization weighted index which assesses the performance of equity securities meeting sustainability standards. Lastly, we utilise the S&P Global ESG Equity & Green Bond Balanced Index to

reflect a performance of a 50/50 stock/bond diversification strategy. All these data is obtained from the S&P Global database.

We also utilise the Chicago Board Options Exchange's (CBOE) Minimum Volatility Index (VIX) as a measure of financial market risk. The CBOE Volatility Index, based on S&P 500 index options, is a real-time market index that gauges how much volatility the market anticipates over the next 30 days. When markets are unstable or the economy is in turmoil, implied volatility generally rises. Consequentially, this index is widely regarded as a measure of market sentiment. We expect a negative correlation between VIX and financial market performance. Figure 1 illustrates the daily market values for all variables.

We create a logarithmic return series for all the time series data sets. Table 1 provides the descriptive statistics of the return series data. Based on the mean values, green equity displays higher daily returns as opposed to the other green instruments. Additionally, the standard deviation indicates that green equity possesses the highest level of variation among the green market. Since the frequency connectedness model adopted in our study begins with a VAR model, we test all data sets for stationarity using the augmented unit root test by Dickey and Fuller (1981). At 5 percent level, the null hypothesis of non-stationarity is rejected for all time series. Thus, we conclude stationarity for all variables.

Lastly, we analyse the correlation matrix that illustrates the pairwise correlations between all variables. Notably, green bonds and green equity possess negative, although weak correlation. Further, in line with our expectations, the risk index has a negative correlation to the green equity market and a positive relation to the green bond. These properties allow us to conclude a relatively negative co-movement between green bonds and green equity. This means the two green investments provide good diversification benefits for investors. However, although the correlation of returns between the various variables provides useful information about the degree to which risks are associated with one another, it provides no information about how risks are transferred between the various variables. Thus, there is still much room for analysis.





Table 1: Descriptive statistics

	GBI	ESG	Balanced	VIX
Minimum	-2.424e-02	0.1276933	0.0601917	0.2998312
Maximum	2.272e-02	0.0914578	0.0332918	0.7682450
Median	6.290e-05	0.0006559	0.0002952	0.0069511
Mean	-6.344e-05	0.0003804	0.0001288	0.0001255
Std dev.	0.003510844	0.01124929	0.005121646	0.07927314
Skewness	-0.5051641	-0.7805477	-1.137867	1.236909
Kurtosis	5.397178	16.09527	14.79991	6.930372
Jarque-Bera	3142.1*	27236*	23354*	5641.6*
ADF	-13.068*	-13.527*	-13.027*	-15.554*
Correlation				
matrix				
GBI	1.000000000			
ESG	-0.019071289	1.000000000		
Balanced	0.182113783	0.018488492	1.000000000	
VIX	0.006934234	-0.328912902	-0.014102446	1.000000000

Notes: The asterisk (*) indicates a rejection of the null hypothesis at 5 percent level of significance.

3.2. Methodology

We utilise a spillover methodology based on the connectedness framework of Diebold and Yilmaz (2012, 2014). In literature, connectedness framework is becoming an increasingly popular methodology to investigate the nexus between various financial markets and/or instruments (Antonakakis & Kizys, 2015; Ahmad, 2017; Ozturk, 2020; Goodell et al., 2022). According to Ahmad (2017), this methodology is more favourable that multivariate GARCH models due to the ability to calculate pairwise net spillovers, as well as determine the direction of spillover. However, ignores the effect of the size and sign of return shocks on the connections between variables and only considers the average-based network of connectedness.

Thus, we will employ a frequency network connectedness model by Baruník and Křehlík (2018), which extends the connectedness framework by quantifying the dynamics of connectivity among a group of variables throughout time and across many frequencies. According to Baruník and Křehlík (2018), financial markets appear to receive information quickly and calmly during times when connection is being formed at high frequencies. Thus, the spillover to one asset in the system will have an impact mostly in the near term. This is an important observation that will form the basis of all analysis in the frequency model.

This method involves implementing a structural vector autoregressive (VAR) model, then obtaining the degree of spillover for all variables involved. The generalized forecast error variance decomposition (GFEVD) of the VAR model serves as the foundation for these spillover estimations. The generalized VAR framework, developed by Koop et al. (1996) and Pesaran and Shin (1998), and used as the foundation for the Diebold-Yilmaz technique, estimates the amount and direction of connectedness in the temporal domain. Thus, we will firstly estimate a VAR(p) model in which:

$$y_t = \sum_{s=1}^p \Phi_j y_{t-s} + \varepsilon_t \tag{1}$$

In accordance with Diebold (2012, 2014), the connectivity metric is derived from the generalized forecast error variance decomposition (GFEVD) of the estimated VAR model. The H-step ahead GFEVD is:

$$\phi_{ij}(H) = \frac{\sigma_{jj}^{-1} \sum_{h=0}^{H} \left((\Psi_h \Sigma)_{ij} \right)^2}{\sum_{h=0}^{H} \Psi_h \Sigma \Psi_h^T}$$
(2)

Thus, the proportion of the variation of the forecast error in variable i that variable j, also known as the directional spillover measure, is:

$$\widetilde{\phi}_{ij}(H) = \frac{\phi_{ij}(H)}{\sum_{j=1}^{n} \phi_{ij}(H)}$$
(3)

Once these measures are obtained, we can measure net directional spillovers and total spillover. The total spillover measure is the average of the cross-variable spillovers. The net directional spillover and total spillover of other variables, i, on variable j are expressed by Equation 4 and 5, respectively:

$$NS_{i \to j}(H) = \widetilde{\phi}_{ij}(H) - \widetilde{\phi}_{ij}(H)$$
(4)

$$TS(H) = \frac{\sum_{i,j=1; j\neq i}^{n} \widetilde{\emptyset}_{ij}(H)}{\sum_{i,j=1; j\neq i}^{n} \widetilde{\emptyset}_{ij}(H)} \times 100 = \frac{\sum_{i,j=1; j\neq i}^{n} \widetilde{\emptyset}_{ij}(H)}{n} \times 100$$
(5)

The frequency connectedness approach by Baruník and Křehlík (2018) allows us to analyse the connectedness across various frequency bands. The GFEVD for a particular frequency, k, is:

$$\phi_{ij}(k) = \frac{\sigma_{jj}^{-1} \sum_{h=0}^{\infty} \left(\left(\Psi(e^{-ikh}) \Sigma \right)_{ij} \right)^2}{\sum_{h=0}^{\infty} \left(\Psi(e^{-ikh}) \Sigma \Psi(e^{ikh}) \right)_{jj}}$$
(6)

Thus, with a specific frequency, k, the directional spillover from j to i is:

$$\widetilde{\phi}_{ij}(k) = \frac{\phi_{ij}(k)}{\sum_{j=1}^{n} \phi_{ij}(k)}$$
(7)

For a certain frequency band, w = (a, b), the directional, net directional, and total spillover of other variables, *i*, on variable *j* can be expressed respectively as:

$$\widetilde{\emptyset}_{ij}(w) = \int_{a}^{b} \widetilde{\emptyset}_{ij}(k) \, dk \tag{8}$$

$$NS_{i \to j}(w) = \widetilde{\phi}_{ij}(w) - \widetilde{\phi}_{ij}(w)$$
(9)

$$TS(w) = \frac{\sum_{i,j=1; j\neq i}^{n} \widetilde{\emptyset}_{ij}(w)}{\sum_{i,j=1; j\neq i}^{n} \widetilde{\emptyset}_{ij}(w)} \times 100 = \frac{\sum_{i,j=1; j\neq i}^{n} \widetilde{\emptyset}_{ij}(w)}{n} \times 100$$
(10)

Lastly, Baruník and Křehlík's method allows us to estimate how each frequency band contributes to each aggregate connectivity measure. The total contribution of a given frequency band, w, to the aggregate spillover is expressed as:

$$TS_{i \to j}(w) = TS_{i \to j}(w) \times \Gamma(w) \tag{11}$$

 $\Gamma(w)$ is the weight of the frequency band on the overall VAR system. Empirically, we express this as:

$$\Gamma(w) = \frac{\sum_{i,j=1;j\neq i}^{n} \widetilde{\emptyset}_{ij}(w)}{\sum_{i,j=1;j\neq i}^{n} \widetilde{\emptyset}_{ij}(\infty)} = \frac{\sum_{i,j=1;j\neq i}^{n} \widetilde{\emptyset}_{ij}(w)}{n}$$
(12)

In this study, similar to prior models such as Pham (2021), we adopt three various frequency bands: 1 to 5 days, 5 to 22 days, and 22 to 66 days. Throughout the paper, we will refer to these as the short-term, medium-term and long-term frequencies, respectively.

4. Empirical Results

4.1. Total Dynamic Connectedness

Figure 2 illustrates the standard dynamic connectivity derived by Diebold and Yilmaz (2012, 2014) between implied risk (VIX) and the green bond market instruments computed on a rolling window of 100 days. The total connectedness ranges between 5 and 60 percent for the balanced fund. The ESG connection range is relatively smaller, only reaching around 55 percent when at its peak. Lastly, both green bonds and green equity have lower total ranges. Through simple inspection, we can analyse that all variables provide peak connectedness during the 2020 period. Prior studies highlight that the peak of the COVID-19 pandemic increased risk globally, causing a decline in the diversification of assets (Ahmad, 2017; Pham, 2021)

Table 2 provides the total spillover measures derived from the FEVD. Since our analysis on the connectedness of financial risk on the performance of green investment, we focus on the fourth column of the spillover table. This column describes the spillover from implied volatility to the various green instruments. Most notably, we observe the relatively large spillover from risk to the green equity index. Contrastingly, the green bond and balanced index have relatively low spillovers, indicating a relatively insignificant risk profile. Thus, in terms of minimising risk, the average rational investor would benefit from a 50/50 green bond and green equity investment portfolio, as opposed to investing in one green investment. This also confirms the diversification properties of the green bond and green equity.

To i	From j						
	GB	ESG	BALANCED	VIX	FROM		
GB	96.46	0.18	3.06	0.31	0.89		
ESG	0.50	86.01	0.18	13.30	3.50		
BALANCED	19.95	0.34	79.47	0.24	5.13		
VIX	0.28	15.66	0.24	83.83	4.04		
ТО	5.18	4.04	0.87	3.46	13.56		

Table 2: Standard spillover measures across

Figure 2: Dynamic spillover between green instruments and implied risk





The frequency extension of the Diebold-Yilmaz method allows us to analyse the Baruník-Křehlík (BK) spillovers of all variables across different frequency ranges. To establish the best green investment strategy, we analyse the spillover from risk (VIX) to the various green investments.

Table 3 illustrates the individual short-, medium-, and long-term spillovers between risk and green bonds, green equity and a balanced fund. In the short term, we find that the largest cross-variable spillovers in the VAR system are attributable to that from risk to green equity. Thus, we can conclude, as with the prior Diebold-Yilmaz measures, that green equity possesses the

most exposure to financial risk. Furthermore, to establish the diversification potential of out green assets, we are relatively small spillovers of risk to green bonds and risk to balanced investment indicates that green bonds provide both less risk that green equity and diversification to green equity.

In the medium term, the BK spillover measures decrease in magnitude. Thus, it is safe to assume that the volatility spillover process within the VAR system decreases with an increased investment horizon. However, the overall spillover remains consistent with our short-term analysis. The green equity market is the most affected by the risk transmission mechanism, with a BK spillover of 2.24 percent. In the long run, a risk-equity spillover of 0.67 is estimated.

Short term: 1 t	to 5 days					
To i	From j					
	GB	ESG	BALANCED	VIX	FROM_ABS	FROM_WTH
GB	71.80	0.09	2.34	0.19	0.66	0.84
ESG	0.42	73.19	0.14	10.22	2.69	3.45
BALANCED	7.33	0.26	62.97	0.2	1.95	2.50
VIX	0.27	11.79	0.16	71.01	3.05	3.91
TO_ABS	2.00	3.04	0.66	2.65	8.35	
TO_WTH	2.57	3.89	0.84	3.40		10.69
Medium term:	5 to 22 d	lays				
To i	From j	From j				
	GB	ESG	BALANCED	VIX	FROM_ABS	FROM_WTH
GB	18.04	0.06	0.43	0.11	0.15	0.93
ESG	0.06	9.31	0.04	2.24	0.59	3.66
BALANCED	8.54	0.02	11.70	0.04	2.15	13.42
VIX	0.01	2.85	0.08	10.56	0.73	4.58
TO_ABS	2.15	0.73	0.14	0.60	3.62	
TO_WTH	13.43	4.57	0.85	3.75		22.59
Long term: 22	to 66 da	vs				
To i	From j					
	GB	ESG	BALANCED	VIX	FROM_ABS	FROM_WTH
GB	5.26	0.02	0.23	0.00	0.06	1.38

Table 3: GFEVD spillover measures acro	oss various	frequency	bands
Table 5. OF EVE Spinover measures activ	USS various	nequency	Danus

ESG	0.02	2.78	0.00	0.67	0.17	3.67
BALANCED	3.23	0.04	3.80	0.00	0.82	17.48
VIX	0.00	0.81	0.00	1.81	0.20	4.38
TO_ABS	0.81	0.22	0.06	0.17	1.26	
TO_WTH	17.39	4.69	1.25	3.59		26.92
Time domain						
To i	From j					
	GB	ESG	BALANCED	VIX	FROM_ABS	FROM_WTH
GB	GB 1.35	ESG 0.01	BALANCED 0.06	VIX 0.00	FROM_ABS 0.02	FROM_WTH 1.40
GB ESG	GB 1.35 0.01	ESG 0.01 0.72	BALANCED 0.06 0.00	VIX 0.00 0.17	FROM_ABS 0.02 0.04	FROM_WTH 1.40 3.67
GB ESG BALANCED	GB 1.35 0.01 0.86	ESG 0.01 0.72 0.01	BALANCED 0.06 0.00 0.99	VIX 0.00 0.17 0.00	FROM_ABS 0.02 0.04 0.22	FROM_WTH 1.40 3.67 17.99
GB ESG BALANCED VIX	GB 1.35 0.01 0.86 0.00	ESG 0.01 0.72 0.01 0.21	BALANCED 0.06 0.00 0.99 0.00	VIX 0.00 0.17 0.00 0.44	FROM_ABS 0.02 0.04 0.22 0.05	FROM_WTH 1.40 3.67 17.99 4.30
GB ESG BALANCED VIX TO_ABS	GB 1.35 0.01 0.86 0.00 0.22	ESG 0.01 0.72 0.01 0.21 0.06	BALANCED 0.06 0.00 0.99 0.00 0.00 0.00	VIX 0.00 0.17 0.00 0.44 0.04	FROM_ABS 0.02 0.04 0.22 0.05 0.33	FROM_WTH 1.40 3.67 17.99 4.30

4.1. Robustness Analysis

As a robustness analysis, we compare the total connectedness from the Diebold-Yilmaz measure to that of the Baruník-Křehlík approach. In doing so, we are able to compare the risk-volatility nexus over the entire series. This will enable us to compare how this relationship fares over various investment horizons. Figure 3, 4 and 5, display the total spillovers for the short, medium and long-term frequencies, respectively. The connectedness measures are obtained using a 100-day rolling window. Our results illustrate that, over the entire life of the VAR system, the connectedness between all the variables is relatively low. However, beginning in 2020, there is a substantial increase in directional spillovers across all frequencies. Intuitively, prior studies attribute this increase to the COVID-19 pandemic's growing financial contagiousness (Pham, 2021; Goodell et al., 2022)

Figure 3: Total spillover for short-term frequency band (1 to 5 days)



Figure 4: Total spillover for medium-term frequency band (5 to 22 days)



Figure 5: Total spillover for medium-term frequency band (22 to 66 days)



Figure 6: Total spillover for medium-term frequency band (time domain)



5. Conclusion

In this era of unprecedented environmental challenges, green investing represents a transformative opportunity to align financial goals with sustainable development objectives. The green financial market is key to establishing financing channels that are aimed at encouraging sustainable development. Sustainable investment funds, green bonds, and impact investing platforms provide avenues for individuals and institutions to invest directly in projects and initiatives with measurable environmental and social benefits.

This paper aimed to establish the best, risk-minimizing green investment strategy by comparing the risk-return nexus between three different investment channels – namely green bonds, green equity and a balanced 50/50 green bond/equity fund. In establishing these effects, we are able to analyse of the diversification potential of all three of these investments. he findings established in this paper surrounding the risk-return nexus of various green investments is key to investors, portfolio managers and policymakers alike.

Firstly, our Diebold-Yilmaz spillover analysis indicates that green bonds and the ESG equity index provide risk diversification benefits for green investors. Further, the lower risk-return spillover on balanced 50/50 bond/equity fund indicates that investors benefit from a diversified strategy, as opposed to a fully allocated bond or equity investment. Further, our frequency spillover estimation allows us to analyse the risk-return connection over various investment horizons. We analyse that, for every green investment strategy, the overall connectedness is significantly higher during the first half of 2020. The connectivity spike as a result of the COVID-19 global pandemic indicates that, in unfavourable market conditions, risk spillovers increase significantly across all market instruments. Thus, we conclude that green bonds and equity provide less diversification benefits during extreme market conditions.

In our frequency connectedness analysis, the spillovers between green bonds and green stock are minimal under typical market conditions. Thus, there is a significant diversification between green bonds and green equity across all frequencies. We draw the conclusion that there are many chances for lucrative hedge and portfolio diversification in the green investment market due to the low interdependence structure green bonds, green equity. Furthermore, the balanced index displays a low risk-return nexus, indicating that green investors are better off by investing in a diversified portfolio. Lastly, under unfavourable market conditions, the green investment market instruments provide little to no diversification against each other.

References

Ahmad, W. (2017). On the dynamic dependence and investment performance of crude oil and clean energy stocks. *Research in International Business and Finance*, *42*, 376-389.

Antonakakis, N., & Kizys, R. (2015). Dynamic spillovers between commodity and currency markets. *International Review of Financial Analysis*, *41*, 303-319.

Bachelet, M. J., Becchetti, L., & Manfredonia, S. (2019). The green bonds premium puzzle: The role of issuer characteristics and third-party verification. *Sustainability*, *11*(4), 1098.

Baruník, J., & Křehlík, T. (2018). Measuring the frequency dynamics of financial connectedness and systemic risk. *Journal of Financial Econometrics*, *16*(2), 271-296.

Chen, Y., & Zhao, Z. J. (2021). The rise of green bonds for sustainable finance: Global standards and issues with the expanding Chinese market. *Current Opinion in Environmental Sustainability*, *52*, 54-57.

Cicchiello, A. F., Cotugno, M., Monferrà, S., & Perdichizzi, S. (2022). Which are the factors influencing green bonds issuance? Evidence from the European bonds market. *Finance Research Letters*, *50*, 103190.

Dickey, D. A., & Fuller, W. A. (1981). Likelihood ratio statistics for autoregressive time series with a unit root. *Econometrica: journal of the Econometric Society*, 1057-1072.

Diebold, F. X., & Yilmaz, 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.

Doğan, B., Trabelsi, N., Tiwari, A. K., & Ghosh, S. (2023). Dynamic dependence and causality between crude oil, green bonds, commodities, geopolitical risks, and policy uncertainty. *The Quarterly Review of Economics and Finance*, *89*, 36-62.

Febi, W., Schäfer, D., Stephan, A., & Sun, C. (2018). The impact of liquidity risk on the yield spread of green bonds. *Finance Research Letters*, *27*, 53-59.

Fernandes, L. H., Silva, J. W., de Araujo, F. H., & Tabak, B. M. (2022). Multifractal crosscorrelations between green bonds and financial assets. *Finance Research Letters*, 103603. Gao, Y., Li, Y., & Wang, Y. (2021). Risk spillover and network connectedness analysis of China's green bond and financial markets: Evidence from financial events of 2015–2020. *The North American Journal of Economics and Finance*, *57*, 101386.

Gavriilidis, K. (2021). Measuring climate policy uncertainty. Available at SSRN 3847388.

Gilchrist, D., Yu, J., & Zhong, R. (2021). The limits of green finance: A survey of literature in the context of green bonds and green loans. *Sustainability*, *13*(2), 478.

Goodell, J. W., Corbet, S., Yadav, M. P., Kumar, S., Sharma, S., & Malik, K. (2022). Time and frequency connectedness of green equity indices: Uncovering a socially important link to Bitcoin. *International Review of Financial Analysis*, *84*, 102379.

Hammoudeh, S., Ajmi, A. N., & Mokni, K. (2020). Relationship between green bonds and financial and environmental variables: A novel time-varying causality. *Energy Economics*, *92*, 104941.

Hu, Y., Bai, W., Farrukh, M., & Koo, C. K. (2023). How does environmental policy uncertainty influence corporate green investments?. *Technological Forecasting and Social Change*, *189*, 122330.

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

Liu, N., Liu, C., Da, B., Zhang, T., & Guan, F. (2021). Dependence and risk spillovers between green bonds and clean energy markets. *Journal of Cleaner Production*, *279*, 123595.

Martiradonna, M., Romagnoli, S., & Santini, A. (2023). The beneficial role of green bonds as a new strategic asset class: Dynamic dependencies, allocation and diversification before and during the pandemic era. *Energy Economics*, *120*, 106587.

Mensi, W., Naeem, M. A., Vo, X. V., & Kang, S. H. (2022). Dynamic and frequency spillovers between green bonds, oil and G7 stock markets: Implications for risk management. *Economic Analysis and Policy*, *73*, 331-344.

Mzoughi, H., Urom, C., & Guesmi, K. (2022). Downside and upside risk spillovers between green finance and energy markets. *Finance Research Letters*, *47*, 102612.

Naeem, M. A., Farid, S., Ferrer, R., & Shahzad, S. J. H. (2021). Comparative efficiency of green and conventional bonds pre-and during COVID-19: An asymmetric multifractal detrended fluctuation analysis. *Energy Policy*, *153*, 112285.

Nguyen, T. T. H., Naeem, M. A., Balli, F., Balli, H. O., & Vo, X. V. (2021). Time-frequency comovement among green bonds, stocks, commodities, clean energy, and conventional bonds. *Finance Research Letters*, *40*, 101739.

Ozturk, S. S. (2020). Dynamic connectedness between bitcoin, gold, and crude oil volatilities and returns. *Journal of Risk and Financial Management*, *13*(11), 275.

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

Pham, L. (2016). Is it risky to go green? A volatility analysis of the green bond market. *Journal* of Sustainable Finance & Investment, 6(4), 263-291.

Pham, L. (2021). Frequency connectedness and cross-quantile dependence between a green bond and green equity markets. *Energy Economics*, *98*, 105257.

Pham, L., & Nguyen, C. P. (2021). Asymmetric tail dependence between green bonds and other asset classes. *Global Finance Journal*, *50*, 100669.

Reboredo, J. C. (2018). Green bond and financial markets: Co-movement, diversification and price spillover effects. *Energy Economics*, *74*, 38-50.

Reboredo, J. C., & Ugolini, A. (2020). Price connectedness between green bond and financial markets. *Economic Modelling*, *88*, 25-38.

Tan, X., Dong, H., Liu, Y., Su, X., & Li, Z. (2022). Green bonds and corporate performance: A potential way to achieve green recovery. *Renewable Energy*, *200*, 59-68.

Teti, E., Baraglia, I., Dallocchio, M., & Mariani, G. (2022). The green bonds: Empirical evidence and implications for sustainability. *Journal of Cleaner Production*, *366*, 132784.

Tiwari, A. K., Abakah, E. J. A., Adekoya, O. B., & Hammoudeh, S. (2023). What do we know about the price spillover between green bonds and Islamic stocks and stock market indices?. *Global Finance Journal*, *55*, 100794.

Umar, Z., Abrar, A., Hadhri, S., & Sokolova, T. (2023). The connectedness of oil shocks, green bonds, sukuks and conventional bonds. *Energy Economics*, *119*, 106562.

Zerbib, O. D. (2016). Is there a green bond premium? The yield differential between green and conventional bonds. *Published in the Journal of Banking and Finance*, *98*, 39-60.

Zerbib, O. D. (2019). The effect of pro-environmental preferences on bond prices: Evidence from green bonds. *Journal of Banking & Finance*, *98*, 39-60.

I acknowledge that I edited this article using Grammarly.