What drives the performance and causality of green bond indices?

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Abstract

This paper empirically assesses the performance of green bond indices and the causality of that performance using a range of financial and commodity data. We present new insights from the novel application of datasets, neural networks and performance measurements. We find that green bond indices do not outperform the market when factors beyond market return are considered. We find that Brent crude oil has the most significant effect on certain indices, a finding that contrasts with other studies on green bonds. A greater sensitivity to oil prices and global green equities also evinces a negative impact on a green bond index's ability to outperform the market. For the first time, a linear causal relationship is established between Title Transfer Facility (TTF) returns and green bond index returns. Additionally, a fundamental shift in causal relationships is observed over the COVID-19 period. In this way, we contribute to the literature on sustainable green bonds and the impact of COVID-19. These insights provide more clarity to market participants for navigating the uncertainties of both the global energy transition and the postpandemic period.

Keywords: Green energy, Green bond indices, Sustainability, Performance analysis, Causal inference, Neural networks, CO2 emission allowances

JEL: C45, C58, G10, G15, L10, Q50

1. Introduction

Sustainability is becoming a key focus of financial markets and regulations, and investors are increasingly interested in financial instruments that comport with sustainable goals. One of the primary financial asset classes that fits this definition is green bonds, which are primed for financing environmentally friendly projects to address climate change (Reboredo, 2018). The United Nations Climate Change Conference (COP26) has restated the need for the mobilisation of $100 billion per year of investment, from both public and private sources, towards decarbonisation and climate change mitigation goals. Green bonds have already proven to be an effective financial instrument capable of raising billions in climate finance (Kanamura, 2020). However, an important aspect of this effort is the involvement of institutional investment, predicated on robust risk management, in green bonds.

Whilst green bonds themselves have been studied with increasing frequency in recent years (Broadstock and Cheng, 2019; Naeem et al., 2021), green bond indices have not received the same attention. The use of bond indices by investors and portfolio managers as a benchmark to measure the performance of both actively and passively managed bond portfolios makes them a prime gauge for the performance of bonds as an asset class. Utilising green bond indices also allows for more readily comparable assessments of performance against other asset classes due to the structure of total return indexation, making green bond index analysis less prone to parameterisation errors, allowing for a streamlined assessment of risk.

Therefore, given that green bonds are a relatively new development and given the growing need for institutional and other professional investors to meet environmental social governance criteria, it is essential that the performance and causality of green bond indices are properly understood. A key challenge in mobilising debt capital towards financing a transition to a low-carbon and climate-resilient (LCR) economy will be managing existing capital constraints given risk and return characteristics. By providing insight into these aspects of green bond indices, we seek to provide market participants and researchers with the clarity to make these judgements. Previous studies have focused on either the performance of green bonds, green bond indices and green equity (Kanamura, 2020; Jin et al., 2020) or on the causality flowing from other asset prices to these asset classes (Hammoudeh et al., 2020).

Most of the limited literature on green bonds and investing relies on investigation of the correlative relationship between markets, and the strand of literature on causality is even more limited. This leads to an inability to legitimately deduce cause and effect on green bond indices, as correlations do not provide a means to detect the specific impact of certain exogenous shocks or regulatory changes. We seek to address this by focusing formally on the causal relationships between our variables, providing practically applicable insights for investors and companies looking to hedge their climate risk exposure.

The objective of this study is to examine the performance of green bond indices and the factors that drive that performance. To this end, we examine four globally significant green bond indices, the iShare Green Index (iSG), Bloomberg Green Index (BG), iShare USD Green Index (iSGC) and S&P Green Index (SPG), using the most prominent and recent performance assessment estimations. The rationale for their inclusion is partly due to their comparable carbon intensity ratings (to ensure like-for-like ESG comparison) and their geographic dispersion of assets (EU, USA, China and Australia). This is crucial for capturing causalities across international markets and contributes to making our findings practically applicable to international investors. Certain indices (iShare USD, Bloomberg Green) are more weighted towards North American firms, whilst the others are more focused on European bonds. This in turn allows us to contrast our findings with previous analyses (Hammoudeh et al., 2020) and provide insights into specific index performance.

We utilise a wide range of data and assess their causal relationships with the indices, including two equity indices, the S&P Clean Index and the EU Renewables Index, and the US 10-year Treasury bill, Brent crude oil and EUA carbon allowance prices. We utilise these variables not just for causality analysis but in combination with performance analysis as well, an investigation not previously conducted in the strand of literature on green bond indices. In addition to oil and carbon allowances, natural gas will continue to be a critical part of the energy mix, and policy-makers and market participants also will have to factor this commodity into any climate financing initiatives. Therefore, for the first time, we assess the causal relationship between the Title Transfer Facility (TTF) natural gas benchmark and green bond index prices, providing insights into the causality of a commodity that is critically important to electricity generation and thereby the energy transition. This is especially true given the ongoing energy crisis that is shifting the balance of the energy complex in Europe (Rehman et al., 2023), driven by acute shortages of natural gas and the need for funding renewable alternatives. By analysing the causality between the TTF and green bond index returns, we can provide avenues for future research into the impact of wholesale commodity prices on the pace of change in the European energy transition. In addition, we can detect how any potential causality may change under uncertainty by conducting robustness tests around breakpoint periods, such as the COVID-19 pandemic. We analyse causality using a blend of econometric and neural network tests with three causality algorithms, the Granger causality, nonlinear Granger causality and transfer entropy algorithms. We also include a novel application of the vector autoregression neural network (VARNN) methodology to leverage the nonlinearity parameters of the artificial neural network (ANN) framework. These tests are chosen to supplement previous results in the literature that focus on Granger causality (Hammoudeh et al., 2020; Lee et al., 2021) and contribute towards broadening the scope of the literature on green bond analysis. We also extend our analysis to look specifically at the effect of the COVID-19 pandemic on green bond indices to assess whether causal relationships established prior to the pandemic still hold, and to the ongoing global energy supply crisis to assess the effect of demand-side exogenous shocks.

In this way, we contribute to the literature by examining the green bond indices with a novel application of various performance analysis and causality tests whilst utilising a dataset that includes a commodity (TTF natural gas) never applied to the study of green bond causality. Our study provides a unique combination of the capital asset pricing model (CAPM), Fama–French 5-factor model and Sortino ratios to define and compare the performance of green bond indices. Our use of VARNN techniques alongside linear and nonlinear Granger causality allows us to supplement previous studies such as Lee et al. (2021). We also contribute by providing a basis for more research on neural network techniques in the green bond space, whilst significantly increasing the available literature on green bond indices themselves. We find that green bond indices do not outperform the market when factors beyond market return are considered. We find that Brent crude oil has the most significant effect on the BG and iSGC indices, a finding that contrasts with other studies on green bonds (Hammoudeh et al., 2020) that demonstrated US Treasury bonds as having the most significant causality. Our transfer entropy results show that green equity index returns provide more influential information than the remaining variables, likely following from the use of fundamental analysis of companies whose bonds compose the green bond indices. A greater sensitivity to oil prices and global green equities also evinces a negative impact on the ability of a green bond index to outperform the market. By investigating the effect of TTF returns on green bond indices, we detect statistical causalities to almost the same extent as with those of Brent crude oil, opening avenues for future research into the economic relationship between green bond indices and natural gas and possible substitution effects from crude oil. We also break our dataset around the structural break of the COVID-19 pandemic and the beginning of the 2021 energy crisis and find evidence that a greater sensitivity to oil prices and global green equities preceded the structural break of the COVID-19 pandemic. In contrast, our analysis during the intra-COVID period suggests a fundamental shift in the causal relationships between our variables and green bond indices, adding to the nascent body of literature on pandemic effects on green bond indices and other financial relationships. Additionally, whilst pandemic-related exogenous shocks have a definite effect on green bond index prices, the current asymmetric energy crisis is evidently disconnected from green bond index return causality.

Our findings create new avenues for further research into the interaction of linear and nonlinear relationships between different indices and market factors. The result that our indices underperform the market provides insight for policy-makers and institutional investors looking to widen their investment in sustainable financial assets and improve market liquidity. We also contribute to the emerging strand in the literature on the effect of COVID-19 on green bonds, providing evidence counter to other studies' assertions regarding the impact of exogenous shocks. In addition, we contribute to the literature on green bond indices through the use of the VARNN model in exploring causality, along with the other models we consider. These insights provide more clarity to market participants for navigating the uncertainties of both the global energy transition and the postpandemic period.

The remainder of this paper is organised as follows. In Section 2, we give a brief overview of the literature, and in Sections 3 and 4, we introduce both our data and our methodology framework. Section 5 provides the empirical results, related discussions and robustness tests. Our paper is concluded in Section 6.

2. Literature Review

Detecting the outperformance of financial assets has been assessed in various ways, but for green bonds, the CAPM and Fama–French 3-factor models are most often utilised. Chu et al. (2020) detect the causal effect of arbitrage limits on various asset pricing anomalies, focusing on stocks. Utilising CAPM and Fama–French estimations to detect outperformance, they found that the anomaly returns and alphas were mostly positive and statistically significant. Baker et al. (2018) study the pricing and ownership patterns of municipal green bonds by incorporating assets with nonpecuniary sources of utility, utilising CAPM. Their results highlighted that green bonds are issued at a premium compared to similar ordinary bonds on an after-tax basis. Lebelle et al. (2020) assess the impact on financial performance from the issuance of green bonds, utilising CAPM and 3- to 4-factor models, with their results suggesting that investors react in a similar manner as with conventional or convertible bonds. Kanamura (2020) examines the greenness character and performance of green bonds in relation to energy and shows evidence of a positive relationship between energy and environmental values. Thus, it is suggested that greenness is incorporated into the Bloomberg Barclays MSCI and the S&P Green Bond Index.

Regarding the relation between green bonds and other financial markets, the literature offers generally limited studies. For instance, Reboredo (2018) reports evidence of significant linkages of these bonds with corporate and government bonds and underscores the benefits of diversification in stock and energy markets. Broadstock and Cheng (2019) investigate the relationship between green and conventional bond markets and find that some macroeconomic factors influence the time-varying relationship between them. Jin et al.

(2020) determine the correlations between carbon markets and green bond indices in the context of hedging using GARCH and OLS parameterisations of dynamic hedge ratio models, showing that the S&P Green Bond Index is the best hedge for carbon futures. Another strand of the literature compares the characteristics of green bonds to those of conventional bonds. MacAskill et al. (2020) use constant and time-varying copulas to examine the dynamic dependence structure between green bonds and several global and sectoral clean energy markets. They show a positive time-varying average and tail dependence between green bonds and clean energy stock markets. Naeem et al. (2021) analyse the connectedness between green bonds and other conventional assets. The principal findings of their study indicate a strong connectedness and spillover effects between green bonds and government and corporate bonds but show a weak connection with high-yield corporate bonds.

Hammoudeh et al. (2020) test the time-varying Granger causality relationship between green bonds and various other financial and commodity variables. It was determined that there was significant causality running from the US 10-year Treasury bond index to green bonds, with significant causality also running from CO2 emission allowance prices and clean energy equity indices, although this was limited to 2019. Lee et al. (2021) test the causal relation between US oil and green bond index prices and geopolitical risks using Granger causality in quantile analysis. Granger causality is detected from geopolitical risk to the oil price at the extreme quantiles, and causality is detected from the oil price to the green bond index for the lower quantiles. Sinha et al. (2021) also utilise quartile modelling, specifically quantile-on-quantile regression and wavelet multiscale decomposition, between the S&P 500 Global Green Bond Index and S&P 500 Environmental and Social Responsibility Index. Green financing mechanisms are shown to have gradual negative transformational impacts on environmental and social responsibility. Their prescription for action includes a potential monitoring mechanism to create sufficient social externalities through the measurement of green project social outcomes.

Given the growing need for institutional and other professional investors to meet environmental social governance criteria, it is essential that the performance and causality of green bonds are properly understood. Previous studies have focused on either the performance of green bonds, green bond indices, and green equity or on the causality flowing from other asset prices to these asset classes. Therefore, the objective of this study is to examine both the performance of green bond indices and the causal relationships between green bond indices and other related assets whilst utilising novel applications of econometric and neural network causality models. Our goal is to provide insights into what factors drive the performance of green bond indices, focusing on the indices rather than the green bonds themselves.

We also extend our analysis to look specifically at the effect of the COVID-19 pandemic on green bond indices to assess whether causal relationships established prior to the pandemic still hold. For this purpose, we include two equity indices, the S&P Global Clean Energy Index and the EU Renewables Index, and the US 10-year Treasury bill, Brent crude oil and EUA carbon allowance prices. Given the critical importance of natural gas in the energy transition, we also assess the causal relationship between the TTF natural gas benchmark and green bond prices. We utilise these variables not only for causality analysis but also in combination with performance analysis. We analyse causality based on three causality algorithms, the Granger causality, nonlinear Granger causality and transfer entropy algorithms, in addition to a novel application of the VAR neural network methodology.

3. Methodological Framework

First, we statistically determine the performance of our four green bond indices via the capital asset pricing model (CAPM), Fama–French 5-factor model and Sortino ratio. Along the lines of Chu et al. (2020), Lebelle et al. (2020) and Baker et al. (2018), the CAPM has been chosen as the primary method of performance analysis for financial assets. However, in contrast to prior studies, we select the Fama–French 5-factor model over the older 3- and 4-factor models previously used in the literature to account for advances in performance analysis and acquire new insights into green bond index performance as an asset class.

3.1 CAPM

The first measure to assess is the capital asset pricing model (CAPM), which highlights that the cost of capital is determined only by systemic risk and generates the required rate of return an investor should expect given the amount of risk that she accommodates. The CAPM provides a measure of the sensitivity of the expected excess green bond index returns against a core global benchmark (the S&P 500) for ease of comparison between the bond indices, some of which contain international bond information. The rationale for using this measure is that it is widely used in the literature (such as in Baker et al., 2018), albeit not with this specific dataset, allowing broad cross comparison, which we augment with additional performance measures.

The CAPM (Sharpe, 1964) has two different components, time value of money (represented by risk-free rate Rf) and systemic risk (represented by β), which compares the returns of the asset to the market over a period of time and to the market premium ($Rm - Rf$). This study uses the S&P 500 as a market to measure the associated risk over a period of time, following the studies of Lebelle et al. (2020) and Baker et al. (2018). Similarly, the excess green bond index return is regressed against the excess of S&P 500 stock returns to examine the associated risk in relation to traditional bonds and stocks. Hence, the specification of the model is as follows.

$$Green\ Bond\ Index\ return - Rf\ =\ \alpha + \beta_1(S\&P500 - Rf) + \theta t \qquad (1)$$

where θt is the error term assumed to be white noise, and Rf is the 1-year US Treasury bill return.

3.2 Fama–French 5-Factor Model

In addition to the CAPM, we utilise the Fama–French 5-factor model (Fama and French, 2015). Whilst the CAPM uses a singular variable to describe the returns of a portfolio or stock over the returns of the market as a whole, the Fama–French model expands to five variables, predicated on the factors determined as driving outperformance, namely, stocks with small capitalisations and stocks with a high book-to-market ratio (“value” stocks, contrasted with “growth” stocks), the return spread between profitable and unprofitable companies (RMW), and the return spread between companies that invest conservatively versus companies that invest aggressively (CMA). These are then added to a CAPM estimation equation:

$$Green\ Bond\ Index\ return - Rf \qquad (2)$$

$$= a + \beta_1(Rm - Rf) + \beta_2 SMB + \beta_3 HML + \beta_4 RMW + \beta_5 CMA$$

where Rf is the risk-free return rate and Rm is the return of the market portfolio as per the CAPM. By including this measure along with the CAPM, we can compare whether the additional factors produce any variance in the results, offering insights into the efficacy of these performance measures for green bond indices. Other studies, such as Chu et al. (2020) and Lebelle et al. (2020), have utilised Fama–French models in conjunction with CAPM to measure green bond index performance; however, these extended only to 3- and 4-factor specifications. Unlike these studies, we seek to add to the strand of literature on the performance measurement of green bond indices by adding the full 5 factors of the most recent literature (Fama and French, 2015).

3.3 Sortino Ratio

The Sortino ratio is a performance measure that differentiates downside deviation from total overall volatility by using the asset's standard deviation of negative portfolio returns instead of the total standard deviation of portfolio returns. The Sortino ratio is able to measure and compare the performance of assets with skewed return distributions by using the downside deviation rather than the standard deviation as the measure of risk. This makes the measure relevant for bond index investors due to their particular focus on duration and short-term yield volatility. Whilst other risk-adjusted indicators do exist, such as the M2 and Sharpe ratios (as applied in Németh-Durkó and Hegedűs, 2021), we utilise the Sortino ratio due to its isolation of the downside volatility of a portfolio or asset. Used in conjunction with the CAPM and Fama–French 5-factor models, this provides a comparable basis against the literature previously mentioned and potential avenues for further research.

$$\text{Sortino ratio} = \frac{R_p - r_f}{\sigma_d} \tag{3}$$

where R_p is the expected portfolio return, r_f is the risk-free rate and σ_d is the standard deviation of the downside. This provides a view of a portfolio's risk-adjusted performance, providing positive volatility is a benefit, delineating an investment's return for a given level of negative risk.

We then perform our causality detection tests on each of our green bond indices, allowing us to determine the extent of causality from our set of financial and commodity data to influence the outperformance of our green bond indices.

The tests that are applied involve a broad segment of causal tests, including linear and nonlinear tests, that are both robust and widely utilised in the strand of literature on bond causality. This allows us to compare and contrast our results with those of different studies (such as Hammoudeh et al., 2020; Lee et al., 2021) and highlight the different results between the linear and nonlinear versions of our tests. We add to this the more recent parameterisation of VARNN and transfer entropy to determine their impact and provide further theoretical underpinning for the study. For similar reasons, we do not apply statistical tests that identify causality between uncorrelated variables, such as convergent cross mapping. More detail covering the mathematical framework of the models can be found in the Appendix.

3.4 Granger Causality

The classical test for causality determined between two series is the Granger (linear and nonlinear) causality test. As defined in Granger (1980), the test is structured to first predict Y with respect to its own history and to then predict with the additional history of a separate variable X. The difference is then evaluated between these two situations, allowing the practitioner to determine whether the added X variable has any effect on the predictions of the target variable.

We select this test to provide a baseline for more modern parameterisations of causality tests (VARNN) and to capture linear and nonlinear causality. This allows us to supplement previous studies that have utilised similar techniques (albeit for different datasets), such as Lee et al. (2021).

3.5 Transfer Entropy

Transfer entropy (Shannon, 1948) measures the information flow from two variables (X to Y) and accounts for both linear and nonlinear causal effects. It should be noted that linear Granger causality and transfer entropy are equivalent if all processes are jointly Gaussian. This allows us to detect simple nonlinear relationships introduced into our dataset with transfer entropy that traditional linear Granger causality may fail to show, and we also can test against other nonlinear tests for robustness (i.e., VARNN).

3.6 VARNN Model

Using artificial neural networks (ANNs), we can detect causality in time series that change nonlinearly over time. It is possible to implement the Granger causality test parameterised as a VARNN model to leverage the nonlinearity parameters of the ANN framework. By selecting this model, in conjunction with transfer entropy, we provide a robust counterpoint to the nonlinear Granger causality, allowing us to critically assess the results from the newer model against established techniques. We also contribute to the literature related to signal processing parameterisation techniques applied to green bond indices (Sinha et al., 2021; Hung, 2021), with our results providing a basis for more research on ANN techniques in the green bond space.

4. Data

For our green bond index data, we select the most prominent traded green bond indices: iShare Green Index (iSG), Bloomberg Green Index (BG), iShare USD Green Index (iSGC) and S&P Green Index (SPG). These securities were selected because they are independently evaluated along four broad dimensions to determine their classification as green bonds. The criteria reflect themes articulated in the International Capital Market Associations ‘Green Bond Principles’, requiring commitments about a bond’s stated use of proceeds, the process for green project evaluation, the process for management of the proceeds and the commitment to ongoing reporting of the environmental performance of the use of the proceeds. The funds themselves are predominantly composed of fixed income securities (such as bonds) with investment-grade creditworthiness, with comparable carbon intensity ratings and geographic dispersion of assets (EU, USA, China and Australia). Certain indices (iShare USD, Bloomberg Green Index) are more weighted towards North American firms, whilst the others are more focused on European bonds. This allows us to contrast our findings with previous analyses of green bonds (Hammoudeh et al., 2020; Naeem et al., 2021) and provide insights into the specifics of index movements. Due to the global nature of our index data, we can capture causalities across international markets, making our results more practically applicable to international investors.

We utilise all available daily price data for each of our indices from 01/08/2014 to 18/10/2021. All data are sourced from Bloomberg. In addition, our causality variables include two equity indices, the S&P Clean Index and the EU Renewables Index, the US 10-year Treasury bill, and the primary traded energy commodity prices: Brent crude oil, TTF natural gas benchmark and EUA carbon allowance prices. The S&P Clean Index and EU Renewables Index represent equity indices, allowing us to analyse the interplay between securities and capital markets in a green energy context, similar to studies such as Broadstock and Cheng (2019) and Reboredo (2018). The S&P Clean Index is weighted primarily towards the US (39.7%) and China (11.7%), whilst the EU Renewables Index provides a contrasting European dataset to address the geographic spread in our green bond indices. Brent crude oil, TTF natural gas and EUA carbon allowance are key global benchmarks for their respective asset classes, meaning that they are comprehensive enough to compare against a variety of green bond indices whilst allowing us to retain a parsimonious dataset. This will allow us to complement the findings of Jin et al. (2020), specifically on the connectedness between green bonds and carbon futures returns. Additionally, by their inclusion, we can study any causal effects of the broader energy commodity complex on green bond indices. Last, the US 10-year Treasury bill is included as a control measure to detect whether our other variables are more or less causal for green bond indices than prevailing interest rates. Our causality variables also are sourced from Bloomberg, specifically daily prices for the 01/08/2014 to 18/10/2021 period. The descriptive statistics for our returns data are displayed in Table 1.

Insert Table 1 about here

All of our data (except the S&P Green Index) have positive mean returns and are covariance stationary at first differences. There is evidence of skewness and leptokurtosis, which motivates a nonlinear approach to contrast with tests that assume a normal distribution. Finally, all the green bond indices have average returns below those of the other asset classes. This suggests that the indices underperform other assets in their class, and we perform an empirical assessment of performance to clarify this.

5. Results

5.1 CAPM, Sortino Ratio and Fama–French Results

First, we present the results of the CAPM estimation for our four green bond indices, where the alpha represents the intercepts and the beta the coefficients of the regression. The results are shown in Table 2. We see that all the alpha estimates are slightly positive, with the exception of the SPG index. However, the alpha estimators are not significant. This suggests that our measure of alpha is highly model dependent, meaning that the CAPM model may not adequately detect latent risk factors and thus may artificially inflate the alpha estimators. This motivates the use of a Fama–French 5-factor model that parameterises latent risk factors to assess performance. The betas of the indices show that all three of the highest-performing indices have the same level of systemic risk. Whilst the Bloomberg Green Index has a lower p value and thereby greater statistical significance, all three are within the 5% confidence interval. This implies that the iShare Green Index has the highest excess return for the lowest level of systemic risk and thus is our outperforming index.

Insert Table 2 about here

The Sortino ratio results show that the BG index has the highest ratio and thus a better risk-adjusted return than the other indices. Additionally, the negative Sortino ratio for the iSG index indicates that the risk-adjusted return is negative. Bearing in mind that the CAPM alpha estimators were not statistically significant, this rationale implies that the index outperforms the others at the expense of higher risk. For the Fama–French estimation results (Table 2), we note that the alpha estimators are negative. They also are highly significant, which implies that they can be accepted over the CAPM. This implies that green bond indices do not outperform the market when factors beyond market return are considered. The beta estimates also are positive compared with those of the CAPM; however, they are much larger, and only the SPG index beta is significant. All of the SMB factors are significant, and the positivity of the SMB coefficients implies that small stocks impact performance more highly. The HML estimators are significant for only the iSG and iSGC indices, and none of the RMW and CMA estimators return significant results.

Together, this implies that green bond indices likely underperform the market portfolio, albeit with factor results that do not fully account for the causality of our indices. This underperformance likely stems from the strong long-term demand for these bonds among green investors, who are increasingly becoming enthusiastic towards addressing their commitments to prevent climate change. As higher demand feeds through to higher prices, this in turn should lower yields on the bonds that constitute the indices, provided that liquidity of supply does not rise with demand. Additionally, underperformance in the short to medium term also is expected, given that investments in green bond indices will reduce margins and profitability. This should be offset by a reduction in risk over the long term, when adverse climate events and other regulations negatively affect companies that have not made suitable investments. To assess more thoroughly the causality of green bond index performance, we now perform causality tests using the variables in our dataset.

5.2 Causality Test Results

Moving to the causality test results, we first perform the Granger causality tests, as shown in Table 3.

Insert Table 3 about here

For Granger causality, we find that we reject the null hypothesis that any of the variables cause a change in the movement of the iSG index. For the BG and iSGC indices, the variable with the most reliably significant effect is Brent crude oil, a finding that contrasts with other studies on green bonds (Hammoudeh et al., 2020) that demonstrated US Treasury bonds as having the most reliable Granger causality. We note that the EUA variable is significant for the SPG index, supplementing prior results in the literature, and may stem from the increased usage and importance of carbon credits in the pricing of financial products in Europe. However, both the S&P Clean and EU Renewable indices also have a positive Granger causality effect for the SPG index, to a greater extent than EUA. This implies that equity market price effects have higher Granger causality than carbon credit price effects on this green bond index.

However, due to the possibility of nonlinear effects, we also perform nonlinear Granger causality tests, which also are presented in Table 3. When we switch to using the nonlinear Granger test, we find that we fail to reject the null hypothesis for all the variables and indices. This implies that there is no nonlinearity to the causal effect of these variables on our index returns. This comes although the indices display high nonnormality of their distribution and thus would be expected to be more receptive to nonlinear testing techniques. We test for the robustness of this via structural break tests to delimitate whether structural changes in our datasets are obscuring the nonlinear informational factors affecting the Granger causality tests. Looking at the remaining statistically significant standard Granger causality results, Brent crude oil has the most significant linear Granger causality for the iSGC index. Together, this implies that a greater sensitivity to oil prices and global green equities has a negative impact on the ability of an index to outperform the market.

Finally, we present the transfer entropy results (Table 4).

Insert Table 4 about here

The transfer entropy results show the extent of information causality flows. For example, the history of the X process (S&P Clean return) has 0.0072 bits of additional information for predicting the next value of Y (the iShare Green Index). That is, it provides information about the future of Y, in addition to what we know from the history of Y.

The transfer entropy results show that all of our variables have nonzero entropy, so we can conclude that all of our variables influence the green bond indices in some way, but the S&P Clean Equity Index provides influential information for more of the indices than the remaining variables, along with Brent crude oil (BG, iSGC and SPG). This may follow from the use of fundamental analysis of companies whose bonds compose the green bond indices, such as the ratio and balance sheet analysis demonstrated in Alonso-Conde and Rojo-Suárez (2018). This would likely have informational effects on bond market participants, thus increasing the influence on green bond returns. In addition, the finding that oil markets provide significant causality confirms the results from the Granger causality tests. Of note is that the TTF is also significant for the SPG index, to almost the same extent as Brent crude oil. This may follow from the increasing importance of natural gas as a transition fuel for addressing global net zero carbon emission commitments and therefore partially determining the price dynamics of green bond indices.

Last, because we are aware that all the aforementioned models could potentially suffer from not fully capturing the nonlinearity of causality in the data, we look to perform VARNN tests, the results of which are presented in Table 5.

Insert Table 5 about here

The results represent the nonlinear outputs from the final layer of the neural network, driven by the optimisation algorithm, which is comparable to the causal relationship demonstrated in the output of the nonlinear Granger causality statistic results above, i.e., the magnitude and sign direction of the output indicate the level and direction of causality. We find that the VARNN results partially confirm the Granger causality results. However, the other variables detect greater causality from the TTF than in the prior tests, with a particularly negative effect detected for the BG index. A possible reason for this is that the VARNN builds on the structure of the Granger causality test, augmenting it by allowing for the modelling of relationships between variables that change over time. Both the Granger causality test and transfer entropy are nonadaptive, meaning they do not make it possible to update the new values by using old ones. However, the VARNN is able to do this, albeit without the presentation of significance variables.

5.3 Results for Testing over the COVID-19 Period

We next seek to determine whether there is any specific effect on green bond index causality due to the COVID-19 pandemic. To this end, we first perform structural break tests to ascertain whether any change in regime took place over the COVID-19 period, and then we rerun our causality testing for both the pre- and intra-COVID periods.

5.3.1 Structural Break Test Results

First, we test for structural breaks in our green bond index data, focusing around 1/1/2020[1]. A Chow test was performed, with the results (shown in Table 6) confirming that there is a structural break in our dataset. From these results, we conclude that for robustness, we should break our dataset to eliminate any interference from the change in year, whilst still capturing the resulting effects of the burgeoning pandemic on financial markets. Second, we test for structural breaks in our green bond index data in 2021. For most of the year, no breaks are detected; however, two of the indices—iSG and iSGC—gave results that allowed us to reject the null hypothesis of no structural break over the period of 5/1/2021. Therefore, we break the dataset for these indices to detect the impact of this specific crisis on green bond indices and whether there is likely to be any lasting effect as the COVID-19 pandemic abates.

5.3.2 Results for the Pre- and Intra-COVID Period Datasets

We now run Granger causality tests for split datasets, focusing on the structural break of the COVID-19 pandemic. The cut-off dates were chosen around 1/1/2020, with the pre-COVID period defined as 1/8/2014 to 1/1/2020 and the intra-COVID period defined as 2/1/2020 to 18/10/2021, in line with the Chow test results.

The results for the pre-COVID dataset are shown in Table 7. Here, we find that the standard Granger causality relationships across the indices have broken down, with almost none of the variables able to explain Granger causality in the indices. We find that the results are largely less statistically significant than in our main results, with the Granger causality providing significant results for only the iSGC index. However, the iSGC index is now mostly caused by the US 10-year Treasury bill, rather than Brent crude oil, which implies that this Granger causality was a phenomenon brought on during the intra-COVID period. This implies that a greater sensitivity to oil prices and global green equities follows the structural break of the COVID-19 pandemic, as if there was no change, and thus it can be assumed that their relationship underwent no adjustment due to the pandemic.

Insert Table 7 about here

[1] We run a series of tests with different cut-off dates from around September 2019 to March 2020 and January 2021 to October 2021; however, our results remain statistically unchanged. We also tested the remainder of the dataset and found no other breakpoints across the indices, and for brevity these results have not been included. The results are available upon request.

We present the results from the intra-COVID datasets in Table 8. Here, we find that the results match much more closely with our main results, namely, that Brent crude oil remains the most significant causal factor across all the indices. We again note that the EUA variable is significant for the SPG index, and both the S&P Clean and EU Renewable indices also have a positive Granger causality effect for the SPG index, to a greater extent than EUA. This implies that these effects came about as a result of the volatility of the COVID-19 pandemic.

Insert Table 8 about here

When looking at the nonlinear Granger causality tests, we find that certain variables display very high levels of causality. This was not broadly the case in our prior results, and the fact that the nonlinear testing now translates to significant results for our remaining indices suggests that during the COVID-19 pandemic, the nature of the causal relationships between our variables and green bond indices has fundamentally shifted. This is likely due to the multifarious impacts of the pandemic on financial markets, such as both fiscal and monetary interventions and increases in alternative energy usage.

This result indicates that green bond indices and their performance are heavily affected by exogenous economic shocks, a finding that runs counter to prior analyses (MacAskill et al., 2020). Again, as in our Granger causality results, Brent crude oil is the most reliably significant, affecting both the BG and iSGC indices. The strength of the causal relationship also is relatively large, which follows from the level of pandemic volatility.

Whilst none of the nonlinear variables are significant for the iSG index, the SPG index shows high causality from the EU Index variable. Given that these results are not uniform, it is plausible that the differences in the internal composition of each index cause different responses to each variable, predicated on how those variables are in turn affected by pandemic-related volatility. The magnitude of these Granger causality statistics suggests that high-volatility events translate to green bond indices, in line with the findings of Broadstock and Cheng (2019) and Reboredo (2018).

Next, we present the transfer entropy results for both the pre- and intra-COVID data samples. The pre-COVID transfer entropy results (Table 9) are broadly in line with the main results. The EU Index and S&P Clean index remain significant for the iSG and BG indices, whilst none of the variables are significant for the iSGC index. In contrast, the SPG index no longer has significant causality from the EU Index and S&P Clean index. Overall, the magnitude of the transfer entropy remains relatively unchanged for variables that remain significant in both samples, implying that the main results held for the prepandemic period. The finding that Brent oil ceases to be a causal factor during the pandemic for the iSGC index is contrary to the findings of Naeem et al. (2021), which implied that connectiveness between green bonds and oil was maintained over the pandemic period.

Insert Table 9 about here

The intra-COVID transfer entropy results (Table 10) show a similar shift in significant variables for the intra-COVID period. This again suggests a breakdown in the prepandemic informational relationship of causality, likely as a result of the wide disruption of financial markets. Of note is the fact that causality for the SPG index has shifted from the TTF to the EUA, and Brent crude oil is no longer significant for the BG. Additionally, the magnitude of the transfer entropy has increased dramatically for all significant variables, except for the S&P Clean for iSGC. This implies that the information flow from these variables has been exacerbated by pandemic effects. The BG index result, however, is less clear, and our results provide routes for further study into the specific pandemic relation between Brent returns and those of the Bloomberg Green Index.

Insert Table 10 about here

Finally, we present the VARNN results for our pre- and intra-COVID datasets in Table 11. The VARNN results for the pre-COVID dataset are significantly lower in their level of causality than in the main results, except for the EUA. The intra-COVID dataset broadly gave higher causality for all indices other than iSG.

Insert Table 11 about here

Overall, we find significant evidence from the Granger causality and transfer entropy results that a shift in the relationship between green bond indices and our causality variables has taken place over the course of the pandemic. This result is in line with recent studies of the pandemic by Naeem et al. (2021) that maintain that the rupture in supply chains and other downstream economic components of the energy industry caused by the pandemic has had a direct effect on energy commodity prices and tertiary industries such as green energy. The heightened informational flow is evidence of this, as is the shift in significant variables. One reason highlighted in Broadstock and Cheng (2019) that could explain this is the interlinking of volatility affects throughout the global energy complex. This opens the potential for volatility-causal investigation of the pandemic on green bonds to determine the exposure of future green energy investments on this facet of potential exogenous shocks.

5.4 Robustness Tests

We now perform a series of robustness tests to confirm that our main results hold. As mentioned, a more robust approach would require the testing of potential structural breaks in our data to determine whether there have been any regimental changes in our variables' causality over time.

5.4.1 Multicollinearity Tests

Given the close correlative relationship between our variables, it is crucial to ensure that the coefficient estimates of the multiple regression do not change erratically in response to small changes in the model or data. Variance inflation factors (VIFs) are a method of measuring the level of collinearity between the regressors in an equation. VIFs show how much of the variance of a coefficient estimate of a regressor has been inflated due to collinearity with the other regressors. They can be calculated by dividing the variance of a coefficient estimate by the variance of that coefficient had other regressors not been included in the equation. The results shown in Table 6 demonstrate that none of the variables has a VIF greater than 2, indicating that we can exclude the potential for multicollinearity.

Insert Table 6 about here

Next, given the economic shock of the COVID-19 pandemic and its effect on financial markets and energy demand, and the impact of massive fiscal intervention from policies such as the EU pandemic emergency purchase programmes, we look to determine whether our results hold when accounting for this structural break in our data. This provides insight as to whether the pandemic has increased the extent to which our variables drive green bond index performance or whether new causal paradigms have emerged. We also perform a structural break test around the ongoing global energy supply crisis in 2021, predicated on a global shortage of natural gas and surging energy demand as countries exit emergency lockdown measures owing to the pandemic.

5.4.2 Results for the Pre- and Intra-Energy Crisis Period Dataset

Next, we examine the results for a second breakpoint, as shown in Table 6. This breakpoint is centred around the ongoing energy supply issues engendered by the aftermath of the COVID-19 pandemic. We perform this analysis to confirm whether any significant results arise and to contextualise our central analysis further, with the results shown in Table 12. The Granger causality results for the precrisis period are mostly in line with the pre-COVID breakpoint dataset results, albeit with lower Granger statistics. This decline also is seen in the transfer entropy statistics, in addition to Brent crude oil becoming statistically significant for the iSG index and the TTF and S&P Clean variables for the iSGC index. This slight shifting of causality between our variables using the brief period between the first and second breakpoints in our dataset indicates the underlying shift in causal relationships as global energy commodities began to regain high demand as economics began to recover from the pandemic.

Insert Table 12 about here

Focusing on the intracrisis results (Table 13), we note that none of the Granger causality or nonlinear Granger causality statistics are significant, in contrast to the intra-COVID results, which detected significance for various energy commodities. Similarly, the transfer entropy and VARNN results lost much of their statistical significance, with the sole exception of S&P Clean for iSG. This suggests that, whilst pandemic-related exogenous shocks have a definite effect on green bond index prices, the current energy crisis is evidently disconnected. This implies that demand-shock energy crises that have traditionally led to precipitous falls in value are not as causal as asymmetric shocks such as COVID-19. However, as the energy crisis overlaps with the COVID period, and considering that the conditions of the pandemic led to the energy crisis, we cannot confirm that this analysis meaningfully supplants that of our central COVID breakpoint analysis.

Insert Table 13 about here

6. Conclusion

In this paper, we empirically assess the performance of green bond indices against market returns, specifically the iShare Green Index (iSG), Bloomberg Green Index (BG), iShare USD Green Index (iSGC) and S&P Green Index (SPG). For the first time, we utilise both CAPM and Fama–French 5-factor performance modelling on these indices, and we find that green bond indices do not outperform the market when factors beyond market return are considered. We analyse the causality for this performance using returns data for green equity, the US T-bill, Brent oil, carbon allowance (EUA) and natural gas (TTF, not previously utilised in the literature) on our green bond indices. We find that Brent crude oil has a significant effect on the BG and iSGC indices, a finding that contrasts with other studies on green bonds (Hammoudeh et al., 2020) that demonstrated US Treasury bonds as having the most significant causality. A greater sensitivity to oil prices and global green equities also evinces a negative impact on the ability of a green bond index to outperform the market. We investigate the effect of TTF returns on green bond indices, and we detect causalities to almost the same extent as with Brent crude oil. This presents the possibility of natural gas markets encroaching on crude oil as a statistically causal determinant in certain green bond indices, a finding not previously highlighted in the literature. This finding presents an opportunity for future research to investigate the possibility of green bond indices and natural gas being related by a third underlying economic factor to clarify the economic causality of this statistical relationship and possible substitution effects from crude oil to natural gas. In addition, we note that the EUA displayed similar levels of causality, supplementing prior results in the literature, which likely stems from the increased usage and importance of carbon credits in the pricing of financial products in Europe. The transfer entropy results show that the S&P Clean Equity Index provides more influential information than the remaining variables, likely following from the use of fundamental analysis of companies whose bonds compose the green bond indices, such as the ratio and balance sheet analysis demonstrated in Alonso-Conde and Rojo-Suárez (2018). Together, this implies that a greater sensitivity to oil prices and global green equities has a negative impact on the ability of an index to outperform the market.

We also break our dataset around the structural break of the COVID-19 pandemic, and the ongoing 2021 global energy crisis, to ascertain the effect of this event on the causal relationships of our data. Looking at the pre-COVID period, we do not find evidence of sensitivity to oil prices and global green equities that precedes the structural break of the COVID-19 pandemic. However, our tests on data through the intra-COVID period suggest that the nature of the causal relationships between our variables and green bond indices has fundamentally shifted since the onset of the pandemic. This likely stems from the unprecedented fiscal and monetary interventions, combined with increased alternative energy usage over the period. Our result that green bond indices and their performance are heavily affected by exogenous economic shocks runs counter to prior analyses (MacAskill et al., 2020) and contributes to the nascent strand of literature on the effect of COVID-19 on sustainable asset classes. We also find nonuniformity among the significance of the causal relationships in our results, implying that the internal composition of the indices causes altering responses to different financial variables, in turn predicated on how those variables are affected by pandemic-related volatility. This result supplements the findings of Broadstock and Cheng (2019) and Reboredo (2018), and future research could consider the impact of reverse causality for these data. Another important finding is that, whilst pandemic-related exogenous shocks have a definite effect on green bond index prices, the current energy crisis is evidently disconnected from green bond index return causality. This insight contributes to the risk management case for green bond indices, as it implies that demand-shock energy crises that have traditionally led to precipitous falls in value are not as causal as asymmetric shocks such as COVID-19.

Our findings create new avenues for further research into the interaction of linear and nonlinear relationships between different indices and market factors. The result that our indices underperform the market provides insights for policy-makers and institutional investors looking to widen their investment in sustainable financial assets and improve market liquidity. We also contribute to the emerging strand in the literature on the effect of COVID-19 on green bonds, providing evidence counter to other studies' assertions regarding the impact of exogenous shocks. Our finding of low causality for our variables over the course of the 2021 energy crisis contributes to the literature on the overhanging effects of COVID-19 and provides insights for market practitioners looking at the reduction in green bond index and climate-related risks over the long term. These insights provide more clarity to market participants, assisting with navigating the uncertainties of both the global energy transition and the postpandemic period.

Disclosure statement

The authors report there are no competing interests to declare.

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Appendix

1. Granger Causality

To conduct the Granger causality test, a pair of vector autoregressive (VAR) models are considered. The first uses the precedent values of Y, and the second uses both passed values of X and Y to predict Y:

$$Model_1 \;\; Y_t = \alpha_0 + \sum_{i=1}^{p} \alpha_i Y_{t-i} + u_t \tag{4}$$

$$Model_2 \;\; Y_t = \alpha_0 + \sum_{i=1}^{p} \alpha_i Y_{t-i} + \sum_{i=1}^{p} \beta_i X_{t-i} + u_t \tag{5}$$

where p is the lag parameter, α_i and β_i are the parameters of the models, and u_t is a white noise error term.

The causality is quantified by evaluating the variances in the errors of both models, in this case with the Granger causality index (GCI), expressed as follows:

$$GCI = \log\left(\frac{\sigma_1^2}{\sigma_2^2}\right) \tag{6}$$

where σ_1^2 and σ_2^2 are the variances of the errors of $Model_1$ and $Model_2$, respectively. For the evaluation of the statistical significance of the differences, the Fisher test can be used, as follows:

$$F = \frac{(RSS_1 - RSS_2) - p}{\frac{RSS_2}{(n-2p-1)}} \tag{7}$$

where RSS_1 and RSS_2 are the residual sum of squares related to $Model_1$ and $Model_2$, respectively, and n is the size of the lagged variables. This leads to two hypotheses:

$$H_0 \colon \forall i \in \{1, \dots, p\}, \beta_i = 0 \tag{8}$$

$$H_1 \colon \exists i \in \{1, \dots, p\}, \beta_i \neq 0 \tag{9}$$

where H_0 is the hypothesis that X does not cause Y. Under H_0, F follows the Fisher distribution with $(p, n-2p-1)$ as degrees of freedom.

2. Transfer Entropy

To avoid the problem of mutual information (wherein common information between X and Y does not consider the information transfer from one variable to the other), time delay parameters are included to specify this direction of information:

$$T_{X\to Y} = \sum_{Y_t, Y_t^q, X_t^p} P\left(Y_t, Y_t^q, X_t^p\right) \log\left(\frac{P\left(Y_t \middle| Y_t^q, X_t^p\right)}{P\left(Y_t \middle| Y_t^q\right)}\right) = I(Y_t, X_t^p | Y_t^q) \tag{10}$$

where $Z_t^l = (Z_{t-1}, \dots, Z_{t-p})$ for $Z = X, Y, p, q$ are the time delay parameters for X and Y, respectively, P represents the probability, and I represents the mutual information symbol.

Another framework for the derivation of transfer entropy can be described as that of the difference between two conditional entropies. In the first instance, Y's past values alone are considered, and in the second, the conjoined past values are added:

$$TE_{X\to Y} = H(Y_t|Y_{t-1},\dots,Y_{t-p}) - H(Y_t|(Y_{t-1},\dots,Y_{t-p}),(X_{t-1},\dots,Y_{t-p})) \tag{11}$$

where H represents the conditional entropy. It is this conjoined expression wherein a prediction principle comparable to that of the Granger causality test is displayed.

3. VARNN Model

The VARNN (p) model is a multilayer perceptron neural network model that predicts the value of the target variable (Y) by way of the target value's own previous values and those of a separate 'predictor' variable. The global function of VARNN (p) can be written as follows:

$$Yt \;=\; \Psi nn\,(\,Y_{t-1},\dots,Y_{t-p},\dots,Y_{k(t-1)}\,,\dots,Y_{k(t-p)}) + \;U_t \tag{12}$$

with a training dataset that consists of a multivariate time series containing one target variable *Y* and *k* predictor variables Y_1,. ., Y_k, where Ψnn is the network function, and Ut represents the error terms.

The remainder of the test is structured similarly to the standard test, as laid out in Aitkin and Foxall (2003). However, since we are using VARNN instead of VAR, two VARNN models must be used as opposed to two VAR models. Accordingly, we change the Fisher test statistic, leading to its definition as follows:

$$F = \frac{\frac{RSS_1-RSS_2}{d_2-d_1}}{\frac{RSS_2}{(n-d_2)}} \tag{13}$$

where d_1 and d_2 are the number of parameters of the univariate and bivariate models, respectively.

Tables

Table 1: Descriptive Statistics of Green bond index and causality variable returns datasets

	Descriptive Statistics			
	Mean	Skew	Kurtosis	ADF p-value
iShare Green Index (iSG)	-0.0003	11.741	713.678	0.000
Bloomberg Green Index (BG)	0.0001	-0.777	13.213	0.000
iShare USD Green Index (iSGC)	0.0001	-1.629	23.776	0.000
S&P Green Index (SPG)	0.0001	-0.518	9.113	0.000
S&P Clean Index	0.0005	-0.478	13.599	0.000
EU Renewables Index	0.0008	-0.452	7.467	0.000
US 10-year Bill	0.0028	0.784	2.078	0.000
Brent crude oil	0.0002	-0.270	16.847	0.000
TTF (Natural Gas)	0.0013	3.152	40.263	0.000
EUA (Carbon Allowance)	0.0016	-0.082	6.353	0.000

Notes: This table shows the descriptive statistics of the iShare Green Index, Bloomberg Green Index, iShare USD Green Index and S&P Green Index, as well as the S&P Clean Index and the EU Renewables Indices, the US 10-year Treasury Bill, Brent crude oil, TTF Natural Gas benchmark and EUA Carbon Allowance data, along with augmented Dickey–Fuller test (ADF) p-values to test against a unit root null hypothesis.

Table 2: CAPM, Sortino Ratio and Fama-French estimation results

	Sortino	CAPM		Fama-French					
		Alpha		Alpha		SMB		RMW	
	Ratio	Estimate	p-value	Estimate	p-value	Estimate	p-value	Estimate	p-value
iSG	-0.03209	0.00006	0.36845	-0.00455	0.00000	0.00059	0.00312	0.00012	0.69444
BG	0.06568	0.00005	0.46719	-0.00455	0.00000	0.00058	0.00399	-0.00016	0.60000
iSGC	0.04957	0.00004	0.49552	-0.00457	0.00000	0.00068	0.00000	-0.00006	0.90201
SPG	0.02359	-0.00006	0.16246	-0.00467	0.00000	0.00038	0.03894	-0.00019	0.51335

		Beta		Beta		HML		CMA	
		Estimate	p-value	Estimate	p-value	Estimate	p-value	Estimate	p-value
iSG		0.00003	0.02714	0.00006	0.52412	-0.00043	0.01511	-0.00030	0.43000
BG		0.00003	0.01454	0.00014	0.17364	-0.00032	0.07254	-0.00006	0.86710
iSGC		0.00003	0.02956	0.00012	0.23884	-0.00039	0.02355	-0.00026	0.49625
SPG		0.00002	0.00611	0.00021	0.03155	-0.00007	0.62787	-0.00034	0.33453

Notes: This table shows the CAPM, Sortino Ratio and Fama-French 5-factor model estimation results for the 4 green bond indices.

Table 3: Granger Causality and Non-Linear Granger Causality tests results

	iSG		BG		iSGC		SPG	
	Granger	p-value	Granger	p-value	Granger	p-value	Granger	p-value
S&P Clean	0.000	0.997	0.002	0.177	0.003	0.060	0.039	0.000
EU Index	0.001	0.268	0.000	0.803	0.001	0.544	0.043	0.000
US 10y	0.001	0.465	0.002	0.132	0.003	0.076	0.001	0.439
Brent	0.002	0.175	0.003	0.042	0.004	0.031	0.002	0.192
TTF	0.000	0.681	0.000	0.945	0.000	0.931	0.001	0.375
EUA	0.001	0.282	0.000	0.844	0.001	0.595	0.026	0.000
	Non-Linear Granger	p-value	Non-Linear Granger	p-value	Non-Linear Granger	p-value	Non-Linear Granger	p-value
S&P Clean	0.010	0.315	0.005	0.880	0.010	0.249	0.002	0.999
EU Index	0.000	1.000	0.002	1.000	0.000	1.000	0.000	1.000
US 10y	0.000	1.000	0.000	1.000	0.000	1.000	0.000	1.000
Brent	0.007	0.619	0.002	0.998	0.000	1.000	0.000	1.000
TTF	0.000	1.000	0.003	0.997	0.003	0.995	0.000	1.000
EUA	0.000	1.000	0.002	1.000	0.000	1.000	0.005	0.904

Notes: This table shows the Granger and Non-Linear Granger Causality (GCI) statistics for the 4 green bond indices using our causality dataset along with test p-values.

Table 4: Transfer Entropy tests results

	Transfer Entropy							
	iSG		BG		iSGC		SPG	
	Transfer Entropy	p-value	Transfer Entropy	p-value	Transfer Entropy	p-value	Transfer Entropy	p-value
S&P Clean	0.007	0.090	0.011	0.003	0.009	0.010	0.010	0.013
EU Index	0.017	0.000	0.006	0.210	0.005	0.277	0.008	0.023
US 10y	0.001	1.000	0.001	1.000	0.002	0.993	0.002	0.983
Brent	0.006	0.213	0.009	0.013	0.009	0.030	0.001	0.000
TTF	0.007	0.173	0.005	0.383	0.005	0.410	0.001	0.012
EUA	0.004	0.613	0.004	0.493	0.004	0.697	0.007	0.107

Notes: This table shows the Transfer Entropy statistics and p-values for the dependent variables of our causality dataset on each of the green bond indices.

Table 5: VARNN Results

	iSG	BG	iSGC	SPG
S&P Clean	0.00009	-0.00073	0.00119	0.00094
EU Index	0.00084	0.00256	0.00026	0.00049
US 10y	0.00019	0.00265	0.00293	0.00289
Brent	0.00063	-0.00073	0.00085	0.00063
TTF	0.00107	-0.01458	0.00606	0.00353
EUA	0.00182	0.00305	0.00101	0.00124

Notes: This table shows the VARNN non-linear output layer results for the dependent variables on each of the green bond indices.

Table 6: Chow test results and Variance Inflation Factors

	Breakpoint 1/1/20		Breakpoint 5/1/21	
Index	F-statistic	P value	F-statistic	P value
iSG	1810.989	0.000	3.632	0.057
BG	2017.704	0.000	0.124	0.725
iSGC	3621.978	0.000	3.797	0.052
SPG	2047.265	0.000	2.116	0.146

Variable	Uncentred VIF	Centred VIF
S&P Clean	1.911	1.909
EU Index	1.847	1.842
US 10y	1.696	1.004
Brent	1.054	1.054
TTF	1.018	1.016

Notes: This table shows the Chow Break test results for each of the green bond indices and the and Variance Inflation Factors for each of the exogenous variables.

Table 7: Pre-COVID Granger Causality and Non-Linear Granger Causality tests results

	iSG		BG		iSGC		SPG	
	Granger	p-value	Granger	p-value	Granger	p-value	Granger	p-value
S&P Clean	0.0022	0.2014	0.0002	0.8442	0.0001	0.9457	0.0014	0.3770
EU Index	0.0004	0.7307	0.0004	0.7483	0.0018	0.2918	0.0009	0.5221
US 10y	0.0038	0.0692	0.0034	0.0965	0.0070	0.0072	0.0016	0.3370
Brent	0.0038	0.0693	0.0002	0.8770	0.0002	0.8734	0.0023	0.2000
TTF	0.0002	0.8864	0.0003	0.2050	0.0010	0.5026	0.0001	0.9601
EUA	0.0003	0.8323	0.0003	0.8071	0.0028	0.1391	0.0005	0.6991
	Non-Linear Granger	p-value	Non-Linear Granger	p-value	Non-Linear Granger	p-value	Non-Linear Granger	p-value
S&P Clean	0.0000	1.0000	0.0000	1.0000	0.0000	1.0000	0.0003	1.0000
EU Index	0.0014	0.1235	0.0009	1.0000	0.0000	1.0000	0.0000	1.0000
US 10y	0.0000	1.0000	0.0001	1.0000	0.0055	0.9580	0.0011	0.9999
Brent	0.0040	0.9931	0.0000	1.0000	0.0005	1.0000	0.0000	1.0000
TTF	0.0001	1.0000	0.0007	1.0000	0.0000	1.0000	0.0000	1.0000
EUA	0.0027	0.9999	0.0007	1.0000	0.0000	1.0000	0.0000	1.0000

Notes: This table shows the Granger and Non-Linear Granger Causality statistics (GCI) using our causality dataset for the 4 green bond indices, along with test p-values for the Pre-COVID dataset.

Table 8: Intra-COVID Granger Causality and Non-Linear Granger Causality tests results

	iSG		BG		iSGC		SPG	
	Granger	p-value	Granger	p-value	Granger	p-value	Granger	p-value
S&P Clean	0.0135	0.0462	0.0105	0.0910	0.0109	0.0823	0.0332	0.0010
EU Index	0.0028	0.5320	0.0055	0.2841	0.0055	0.2862	0.0370	0.0019
US 10y	0.0005	0.8926	0.0002	0.9569	0.0004	0.9141	0.0014	0.7248
Brent	0.0020	0.6397	0.0112	0.0776	0.0153	0.0302	0.0179	0.0166
TTF	0.0006	0.8729	0.0002	0.9594	0.0004	0.9212	0.0040	0.3981
EUA	0.0074	0.1861	0.0566	0.2745	0.0050	0.3201	0.0141	0.0400
	Non-Linear Granger	p-value	Non-Linear Granger	p-value	Non-Linear Granger	p-value	Non-Linear Granger	p-value
S&P Clean	0.0094	0.9988	0.0083	0.9999	0.0000	1.0000	0.0000	1.0000
EU Index	0.0568	0.0661	0.0000	1.0000	0.0000	1.0000	0.0017	0.0456
US 10y	0.0139	0.9852	0.0000	1.0000	0.0000	1.0000	0.0000	1.0000
Brent	0.0049	0.9996	0.3339	0.0010	0.3720	0.0001	0.0143	0.9845
TTF	0.0000	1.0005	0.0000	1.0000	0.0124	0.9921	0.0001	1.0000
EUA	0.0000	1.0005	0.0000	1.0000	0.0249	0.8050	0.0015	1.0000

Notes: This table shows the Granger and Non-Linear Granger Causality statistics (GCI) using our causality dataset for the 4 green bond indices, along with test p-values for the Intra-COVID dataset.

Table 9: Pre-COVID Transfer Entropy tests results

	Transfer Entropy							
	iSG		BG		iSGC		SPG	
	Transfer Entropy	p-value	Transfer Entropy	p-value	Transfer Entropy	p-value	Transfer Entropy	p-value
S&P Clean	0.003	0.873	0.011	0.023	0.006	0.487	0.007	0.170
EU Index	0.022	0.000	0.006	0.396	0.004	0.767	0.009	0.063
US 10y	0.001	0.997	0.001	1.000	0.001	0.997	0.001	1.000
Brent	0.006	0.480	0.008	0.143	0.004	0.896	0.010	0.036
TTF	0.007	0.300	0.005	0.500	0.009	0.103	0.006	0.270
EUA	0.007	0.297	0.004	0.750	0.007	0.353	0.011	0.013

Notes: This table shows the Transfer Entropy statistics and p-values for the dependent variables on each of the green bond indices for the Pre-COVID dataset, using the variables from our causality dataset.

Table 10: Intra-COVID Transfer Entropy tests results

	Transfer Entropy							
	iSG		BG		iSGC		SPG	
	Transfer Entropy	p-value	Transfer Entropy	p-value	Transfer Entropy	p-value	Transfer Entropy	p-value
S&P Clean	0.041	0.001	0.048	0.001	0.048	0.001	0.071	0.001
EU Index	0.039	0.003	0.019	0.197	0.026	0.040	0.026	0.003
US 10y	0.025	0.087	0.002	1.000	0.002	1.000	0.001	1.000
Brent	0.040	0.003	0.023	0.070	0.023	0.047	0.037	0.001
TTF	0.018	0.220	0.005	0.977	0.006	0.883	0.010	0.580
EUA	0.015	0.337	0.012	0.587	0.015	0.320	0.020	0.040

Notes: This table shows the Transfer Entropy statistics and p-values for the dependent variables on each of the green bond indices for the Intra-COVID dataset, using the variables from our causality dataset.

Table 11: VARNN Results for Pre- and Intra-COVID datasets

	Pre-COVID				Intra-COVID			
	iSG	BG	iSGC	SPG	iSG	BG	iSGC	SPG
S&P Clean	0.0001	-0.0011	-0.0011	0.0000	-0.0006	-0.0007	-0.0006	-0.0002
EU Index	0.0005	-0.0003	-0.0003	0.0004	0.0045	0.0045	0.0044	0.0040
US 10y	0.0034	0.0030	0.0030	0.0034	0.0008	0.0008	0.0008	0.0009
Brent	0.0009	-0.0098	-0.0098	-0.0003	-0.0004	-0.0005	-0.0004	0.0001
TTF	0.0027	-0.0337	-0.0337	-0.0017	-0.0105	-0.0103	-0.0098	-0.0076
EUA	0.0011	0.0063	0.0063	0.0016	0.0044	0.0044	0.0043	0.0041

Notes: This table shows the VARNN non-linear output layer results for the dependent variables on each of the green bond indices, for both the Pre- and Intra-COVID datasets.

Table 12: Pre-Crisis Granger Causality, Transfer Entropy and VARNN results

	iSG		iSGC		iSG		iSGC	
	Granger	p-value	Granger	p-value	Transfer Entropy	p-value	Transfer Entropy	p-value
S&P Clean	0.0001	0.4455	0.0073	0.0019	0.0090	0.0571	0.0142	0.0000
EU Index	0.0003	0.8083	0.0006	0.6191	0.0208	0.0000	0.0071	0.1800
US 10y	0.0035	0.0531	0.0025	0.1253	0.0006	1.0000	0.0018	0.9971
Brent	0.0035	0.0537	0.0032	0.0711	0.0092	0.0372	0.0068	0.2132
TTF	0.0001	0.9040	0.0013	0.3351	0.0073	0.1271	0.0104	0.0171
EUA	0.0002	0.8759	0.0018	0.2193	0.0035	0.8000	0.0053	0.4270
	iSG		iSGC		iSG	iSGC		
	Non-Linear Granger	p-value	Non-Linear Granger	p-value	VARNN	VARNN		
S&P Clean	0.0000	1.0000	0.0168	0.0351	0.0010	0.0010		
EU Index	0.0005	1.0000	0.0000	1.0000	0.0005	0.0006		
US 10y	0.0000	1.0000	0.0000	1.0000	0.0033	0.0033		
Brent	0.0029	0.9961	0.0000	1.0000	-0.0098	-0.0093		
TTF	0.0000	1.0000	0.0000	1.0000	0.0065	0.0063		
EUA	0.0021	0.9999	0.0000	1.0000	-0.0072	-0.0068		

Notes: This table shows the Granger and Non-Linear Granger Causality statistics (GCI), Transfer Entropy and VARNN non-linear output layer results using our causality dataset for the Pre-Crisis dataset.

Table 13: Intra-Crisis Granger Causality, Transfer Entropy and VARNN results

	iSG		iSGC		iSG		iSGC	
	Granger	p-value	Granger	p-value	Transfer Entropy	p-value	Transfer Entropy	p-value
S&P Clean	0.0021	0.8149	0.0175	0.1866	0.0368	0.0333	0.0178	0.3533
EU Index	0.0005	0.9544	0.0079	0.4595	0.0099	0.8975	0.0109	0.8071
US 10y	0.0005	0.9544	0.0079	0.4595	0.0000	1.0000	0.0000	1.0000
Brent	0.0005	0.9544	0.0018	0.8344	0.0130	0.6232	0.0128	0.5831
TTF	0.0060	0.5511	0.0119	0.3113	0.0000	1.0000	0.0132	0.5000
EUA	0.0029	0.7535	0.0228	0.1065	0.0128	0.6878	0.0129	0.5900
	iSG		iSGC		iSG	iSGC		
	Non-Linear Granger	p-value	Non-Linear Granger	p-value	VARNN	VARNN		
S&P Clean	0.0000	1.0000	0.0528	0.8821	-0.0023	-0.0021		
EU Index	0.0000	1.0000	0.0000	1.0000	-0.0029	-0.0025		
US 10y	0.0000	1.0000	0.0000	1.0000	0.0000	0.0000		
Brent	0.0000	1.0000	0.0000	1.0000	0.0029	0.0027		
TTF	0.0000	1.0000	0.0000	1.0000	0.0034	0.0046		
EUA	0.0781	0.5721	0.0000	1.0000	0.0243	0.0215		

Notes: This table shows the Granger and Non-Linear Granger Causality statistics (GCI), Transfer Entropy and VARNN non-linear output layer results using our causality dataset for the Intra-Crisis dataset.