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# Factors behind the performance of green bond markets☆

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ABSTRACT

The market for green bonds has grown dramatically over the past several years, necessitating an understanding of the variables that might forecast its performance. Studies on how the green bond market interacts with other markets are widely discussed in the literature, but little is known about the variables that improve predictions of green bond returns. In this study, we use data on commodity and financial asset prices, as well as speculative factors, to predict the returns on green bonds using the Feasible Quasi-Generalized Least Squares (FQGLS) and the causality-in-quantiles estimators. The findings demonstrate that most factors are significant predictors of the returns on green bonds, with speculative factors having a detrimental predictive influence, and commodity and financial asset prices having a mixed predictive impact. When asymmetries are taken into account, the asymmetric predictive model performs better at predicting the returns on green bonds than its symmetric counterpart in most instances. Finally, all the factors, except investors' sentiment, affect the returns on green bonds in a variety of market situations. The interdependence among the global financial and commodity markets, as well as economic uncertainties justify the established predictive influence, since green bonds are a component of the broader investment bonds.

## 1. Introduction

This paper provides further insight into the hedging potential of green bonds by investigating the predictive power of several assets, speculation, and uncertainties on the performance of the green bond market. In recent years, green bonds, under the concept of green finance, have been widely adopted by governments and investors in financial markets (Reboredo et al., 2020). By definition, green bonds are fixed-income investments, funding eco-friendly projects. The idea was first introduced by the European Investment Bank in 2007 as a solution to recurring environmental crises, and has grown in popularity over time. These financial instruments raise capital in the bond market, similar to ordinary non-green bonds, and they use green assets and projects to increase long-term liabilities from various investors (Weber & Saravade, 2019). One of the unique characteristics of green bonds is that the revenues from these bonds finance eco-friendly projects, promote the use of low-carbon energy and benefit global climate crises (Gianfrate & Peri, 2019; Nguyen

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et al., 2020). Meanwhile, the green bond markets have made great progress in terms of benefits for both stakeholders and nations over the past decade, due to the important role they play in financing environmentally friendly projects and thus contributing to reducing the adverse effects of climate change (Hammoudeh et al., 2020; Reboredo et al., 2020). Glomsrød and Wei (2018) emphasize that green bonds reduce global coal consumption, thereby increasing the share of non-fossil electricity, which is a way of further reducing global $CO_2$ emissions. Since the time of their introduction to the global financial market, their market price has grown from $0.8 billion to $257.7 billion as of 2019 with 62 countries issuing green bonds in 2019 (Climate Bonds Initiative, 2019). In a more recent media release, the volumes of green and other labelled bonds had reached $417.8 billion as at the first half of 2022, with the cumulative green bond issuance being $1.9 trillion (Climate Bonds Initiative, 2022).

The phenomenal development of the green bond market has gained considerable attention from both scholars and the investment community. Several studies focusing on the price connectedness between green bond markets and global financial markets have emerged in the finance and economic literature. Some studies focus on the co-movement between green bond and other asset classes (Broadstock & Cheng, 2019; Ferrer et al., 2021; Hammoudeh et al., 2020; Kanamura, 2020; Reboredo, 2018). Other studies also examine volatility spillover effects between green bond and traditional assets classes (Guo et al., 2021; Le et al., 2021; Naeem, Nguyen, et al., 2021; Tiwari, Abakah, Adekoya, & Hammoudeh, 2021). Recently, an emerging strand of studies highlights the safe haven or diversification benefits of green bond markets (Arif et al., 2021; Pham, 2021; Pham & Nguyen, 2022; Reboredo, 2018). Interestingly, even though several emerging studies on the behavior of the green bond market relative to conventional assets have been analyzed from different perspectives, leading to a comprehensive emerging literature, several questions remain unanswered on the potential diversification benefits of green bonds. For example, the relationship between the green bond market and global uncertainties and diverse commodities, other than energy commodities, is underscored by limited empirical evidence.

Given that the problems of environmental degradation and climate change that the issuance of green bonds is intended to address result from multiple sources, the green bond market can also be driven by multiple factors. Anh Tu et al. (2020) acknowledge that the expansion of the green bond market is dependent on a number of influencing variables that need to be prioritized. The role of policy uncertainties in driving macroeconomic instabilities have been widely debated among policy makers, academics and practitioners. Policy uncertainty can affect the decisions and behavioral pattern of economic agents since it can distort the environmental conditions in which firms and individuals operate. Moreover, Jiang et al. (2019) advocate that policy uncertainty contributes to carbon emissions through government directives and policies that might encourage or obstruct ecological dilapidation. Accordingly, it is possible for policy uncertainty to have an effect on carbon emissions (Jiang et al., 2019) and, by implication, the financial instruments that are introduced to mitigate it. In another regard, policies that keep investors informed about green bonds have the ability to influence investment incentives in the market, thereby yielding another channel through which the requirements for financing towards a transition to a carbon-friendly economy can be achieved (Pham & Huynh, 2020). It then follows that the way investors feel about the green investment market, popularly known as investor sentiment, and the uncertainty that characterizes their choices have a lot to do with the performance of the green bond market, and should be given a careful consideration (Piñeiro-Chousa et al., 2021). Also, the mining and the consumption of commodities have consequential effects on environmental quality through carbon emissions. With the increasing financialization of commodities in recent years, their use brings about fluctuations in prices. If the price changes are favorable, the commodities may attract investors away from investing in green assets, thereby affecting the green bond market. This is demonstrated by Gormus et al. (2018) who reveal that the overall high-performing bond (including the green bond) market is impacted by the energy markets from the point of view of price and volatility. The story is not different for the traditional financial markets, of which the commodity markets are also fast becoming a part. The discount rate channel (Reboredo, 2018; Yan et al., 2022) and the contagion or risk transmission effect that characterize diverse financial markets (Reboredo & Ugolini, 2020) provide the mechanism through which the green bond market can be associated with the traditional financial markets.

In light of the complex interaction of the green bond market with several indicators, it is certain that there would be variance in the reaction of the former to the latter. It is therefore necessary to determine how various financial, economic, commodity, and uncertainty factors can predict the green bond returns in order to offer investors the wisdom needed for portfolio management and diversification purposes. While a handful of studies have attempted to connect some of these influencing factors with the green bond market, there are still significant limitations. Despite the theoretical foundation that connects a wide range of these influencing variables to green bonds, quite a large number of them are yet to be empirically analyzed, especially within the context of forecast analysis. Rather, the majority have focused on mere connectedness (see Naeem, Adekoya, & Oliyide, 2021; Arif et al., 2021; Nguyen et al., 2020; Reboredo et al., 2020; Reboredo & Ugolini, 2020, etc.). In addition, given that the financial and commodity asset prices, and uncertainty indicators are often subject to extreme oscillations, the need for capturing asymmetries in the forecast nexus becomes non-negotiable. Unfortunately, there is another huge gap in the literature in this regard. Therefore, to significantly extend the existing body of knowledge, this paper assesses the predictive power of 17 influencing factors, cutting across the three major categories, namely commodities, financials, and uncertainties.

Specifically, this study adds to the literature in several ways. First, we investigate the predictive power of different commodity and financial asset classes and uncertainties in forecasting the performance of the green bond market. Second, we utilize a large pool of 17 predictors, making this study the most comprehensive analysis of the performance of the green bond market in the literature. We particularly acknowledge the studies of Naeem et al. (2022), Nguyen et al. (2020), and Arif et al. (2021), but the present study is quite unique in its objectives, consideration and approach. Naeem, Adekoya, and Oliyide (2021) merely examine the risk spillovers among the underlying assets, rather than making known the ability of other indicators to predict and forecast green bond returns. Moreover, the choice of variables used by the authors are aggregated indices, such as the energy index, the precious metal index, and the world stock index. The problem with such measurements is the aggregate bias they tend to induce given that, in the real sense, economies and financial markets may not necessarily behave similarly every time. Disaggregated measures of indices provide clearer direction for policy implementation and investment decisions. In addition, the role of uncertainties in economic policies and financial markets are not considered. The studies of Arif et al. (2021) and Naeem, Adekoya, and Oliyide (2021) are similar to that of Naeem, Adekoya, and Oliyide (2021), except that the connectedness approaches employed by them account for investment frequency. Nonetheless, the fact remains that none of these studies is concerned with the predictability and forecast of green bond returns with the highlighted indicators. They also fail to bring the distinct influence of the predictors to fore, nor the role of uncertainties. Our first predictability test is based on the approach of Westerlund and Narayan (2015), which is consistent with the presence of serial correlation, conditional heteroskedasticity, persistence and endogeneity. The statistical features are commonly associated with financial series, and can lead to spurious results if not addressed. Last but not least, we take a further step to determine the predictive power of the predictors across different quantiles. This form of analysis helps to determine the performance of the green bond market at different market conditions, such as when the market is normal, bearish or bullish.

The remainder of the paper is organized as follows: Section 2 offers a review of the studies, Section 3 develops the methodology and presents the data, and Section 4 discusses the empirical results. The conclusion and policy implications follow in Section 5.

## 2. Literature review

Green bonds, gaining international acknowledgment, have recently become a phenomenon in the literature. However, the scientific literature on green bonds is limited. Literature related to our study explores the relationship between the green bond market and other assets. For example, Pham (2016), analyzing the volatility dynamics between different bond markets, reveals evidence of volatility clustering in the green bond market and spillover from the traditional bond market. Reboredo (2018) finds that while moving quite similarly with the treasury and corporate bond markets, the green bond market provides opportunities for diversification for investors in the energy and stock market. Reboredo and Ugolini (2020) investigate the price relationship between the green bond market and other financial markets. The findings show that green bonds are closely related to currencies and fixed income markets, where the green bond market is a net recipient of volatility shocks in both major markets. Conversely, it is found that the bond market has weak links with the stock, energy and high-return corporate bond markets. Additionally, Le et al. (2021), in the age of the 4th industrial revolution, examine the time and frequency domain connectedness and spillover among green bonds, fintech and cryptocurrencies with results suggesting that green bonds are net receivers of volatility shocks from bitcoin, equities and fintech stocks. Saeed et al. (2020) investigate the potential of green stocks and bonds to protect dirty assets, and Huynh et al. (2020) examine the diversifying function of green bonds. Similarly, Reboredo et al. (2020) find a strong link between the green bond market and treasury and corporate bonds in the US and EU countries. Nguyen et al. (2020) suggest the potential diversification of green bond markets following the low and negative correlations between green bonds and stocks and commodities.

Another recent study of Hammoudeh et al. (2020) suggests that financial and environmental stocks affect green bonds over different time scales. Naeem, Adekoya, and Oliyide (2021) document that green bonds can act as a good hedge against industrial metals, agricultural commodities and natural gas markets. Arif et al. (2021) study the diversifier, safe-haven, and hedging properties of Green Bonds for fixed income, equity, forex, and commodity by using the cross-quantilogram test. Their full sample results indicate that Green Bonds could serve as diversifier assets for equity investors, while they could serve as a hedging and safe-haven instrument for currency and commodity investments. Meanwhile, their results based on a sub-sample show a heightened lead-lag relationship between Green Bonds and returns of forex investments. Ferrer et al. (2021) examine the interdependence between Green Bonds and green stocks by considering assets such as treasury, investment-grade, corporate bonds, general stocks, crude oil, and gold. The results reveal the linkage of Green Bonds to treasury and investment-grade corporate bonds, while green stocks are strongly connected to general stocks.

This paper provides fresh evidence on the performance of green bonds by showing how the performance of the green bond market can be predicted by a broad range of factors including commodities, conventional and alternative financial assets and uncertainties. While, to some extent, some common commodity and financial series have been investigated in relation to the green bond market, little evidence is empirically established for different uncertainty indicators, such as financial market uncertainty, economic policy uncertainty and investor sentiments. We examine the impact of global uncertainties on green bond price variation for various reasons. Global uncertainties have been described by extant studies as key drivers of economic outcomes (Blattman & Miguel, 2010; Fernandez & Rodrik, 1991; Guidolin & La Ferrara, 2010).

As mentioned earlier, a number of emerging studies investigate the dynamics between green bonds and global financial markets using various estimation techniques to test volatility transmission and coherency. For example, Reboredo (2018) employ the copula functions to examine price connectedness between green bond market and financial market while, Le et al. (2021), Reboredo et al. (2020) and Saeed et al. (2020) rely on different spillover techniques. To the best of our knowledge, this is the foremost paper that provides a comprehensive analysis on the performance of green bond under the condition of uncertainties and a large pool of conventional asset classes.

## 3. Methodology and data

### 3.1. *Westerlund and Narayan (2015) predictive model*

We are motivated to employ Westerlund and Narayan's (2015) predictive model because of its associated merits, a standard by which many other predictive models fall short. Common among financial and economic series are the problems of serial correlation, conditional heteroscedasticity, persistence, and endogeneity, which often undermine empirical results. By way of demonstration, Lewellen (2004) proves that not accounting for the persistence effect when it is present can underestimate the outcome of the predictor, whereas forecast accuracy is improved with accounting for such in a predictive model. Building on this, Westerlund and Narayan (2012, 2015) further argue that with the evidence of conditional heteroscedasticity that characterizes high-frequency series, forecast estimates may lose precision even when the persistence effect has been controlled for. The challenge with endogeneity and serial correlation is that they can also impose biases on parameter estimates if not accounted for, with the latter particularly overestimating or underestimating the standard errors. The strength of Westerlund and Narayan (2015) is seen in their accounting for all these concerns in producing reliable estimates for proper inferences.

The first part of the methodology deals with the predictive model of Westerlund and Narayan (2015). As such, we commence by specifying the bivariate relationship between a variable, $x$, called the predictor, and another variable, $y$:

$$y_t = \alpha_0 + \beta_0 x_t + \varepsilon_t, \tag{1}$$

where $x_t$ stands for any of the commodity returns, financial asset returns and the speculative factors, while $y_t$ represents green bonds returns. $\varepsilon_t$ is the disturbance term that is assumed to be normally distributed.

Equation (1) is then estimated in line with the approach of Westerlund and Narayan (2015). Suitably, the approach builds on the initial predictive model of Lewellen (2004) which accounts for endogeneity and persistence by arguing that the forecast estimates can still be biased in the presence of serial correlation and heteroskedasticity. Therefore, the new model is able to produce reliable estimates in the presence of all the four undesirable factors, namely persistence, endogeneity, heteroskedasticity and serial correlation. Accounting for endogeneity and persistence, the first-order autoregressive term of the predictor is included in the model so as to obtain a bias-adjusted estimate (Lewellen, 2004):

$$y_t = \alpha_0 + \beta_{10} x_{t-1} + \beta_{20}(x_t - \delta_0 x_{t-1}) + \mu_t \tag{2}$$

$$\widehat{\beta}_{10}^{adj} = \widehat{\beta}_{10} - \beta_{20}(\widehat{\delta}_0 - \delta_0), \tag{3}$$

where $\delta_0$ and $\widehat{\delta}_0$ are the actual and fitted estimates of the immediate lagged value of the predictor, $x$. $\mu_t$ is the new disturbance term after the additional term, $\beta_{20}(x_t - \delta_0 x_{t-1})$ has been included to correct for any inherent endogeneity bias, with $\widehat{\beta}_{10}^{adj}$ being the bias-adjusted estimator of $\beta_{10}$.

Equation (2) is now re-specified to include $\widehat{\beta}_{10}^{adj}$:

$$y_t = \alpha_0 + \widehat{\beta}_{10}^{adj} x_{t-1} + \beta_{20}(x_t - \delta_0 x_{t-1}) + \mu_t, \tag{4}$$

In a bid to correct for the biasness resulting from serial correlation and heteroskedasticity, Westerlund and Narayan (2015) propose the pre-weighting of all the series by $1/\widehat{\mu}_t$. The resultant equation is then estimated using the ordinary least square (OLS) technique. The OLS estimator is obviously a modified version, termed the Feasible Quasi-Generalized Least Squares (FQGLS) estimator. It is specified as:

$$t_{FQGLS} = \frac{\sum_{t=q_m+2}^{T} \widehat{\tau}_t^2 y_t^d x_{t-1}^d}{\sqrt{\sum_{t=q_m+2}^{T} \widehat{\tau}_t^2 (x_{t-1}^d)^2}}, \tag{5}$$

where the weighting factor is $\widehat{\tau}_t = 1/\widehat{\sigma}_{\mu,t}$. $x_t^d$ and $y_t^d$ denote the demeaned series of $x$ and $y$ respectively.

We take one step further to determine if asymmetries are essential in the predictive nexus. To do this, the predictor, $x$, is decomposed positive ($x_t^+$) and negative ($x_t^-$) partial sums in line with Shin and Greenwood-Nimmo (2014). The decomposition is illustrated as follows[1]

$$x_t^+ = \sum_{j=1}^{t} \Delta x_{ij}^+ = \sum_{j=1}^{t} \max(\Delta x_{ij}, 0) \tag{6a}$$

$$x_t^- = \sum_{j=1}^{t} \Delta x_{ij}^- = \sum_{j=1}^{t} \min(\Delta x_{ij}, 0)\ . \tag{6b}$$

The asymmetric version of the equation is then given as:

$$y_t = \alpha_0 + \widehat{\beta}_{10}^{adj} x_{t-1}^+ + \widehat{\beta}_{11}^{adj} x_{t-1}^- + \beta_{20}(x_t^+ - \delta_0 x_{t-1}^+) + \beta_{21}(x_t^- - \delta_0 x_{t-1}^-) + \mu_t\ . \tag{7}$$

Asymmetry matters and should be put into consideration if either or both the asymmetric terms are statistically significant.

For the main forecast evaluation, the formal Campbell and Thompson [C-T hereafter] (2008) test is used. The C-T test is a forecast test that flexibly compares the performance of two nested models, i.e. the unrestricted and the restricted models. Its statistic is

[1] See Shin and Greenwood-Nimmo (2014) for a full description of the decomposition process. Studies including Adekoya (2021) and Salisu and Isah (2018) have also used similar decomposition approach in the predictability studies.

computed as:

$$C - T = 1 - \left(\frac{M\widehat{S}E_1}{M\widehat{S}E_2}\right), \tag{8}$$

where $M\widehat{S}E_1$ and $M\widehat{S}E_2$ respectively stand for the mean square errors of the unrestricted and the restricted models. If the statistic is positive, the unrestricted model performs better than the restricted model, and otherwise if it is negative.

### 3.2. Nonparametric causality-in-quantiles method

The other advanced technique employed in this study is the nonparametric causality-in-quantiles technique whose merits, among others, have to do with its strong predictive power in the presence of non-linearity, regime changes and structural breaks. Intuitively, the estimate provided at different quantiles can be used to interpret the predictive nexus at different market conditions, i.e. bearish, normal and bullish market periods. For this reason, we employ the causality-in-quantiles test of Balcilar et al. (2016, 2017) and report only the causality-in-mean results. Essentially, Balcilar et al. (2016, 2017) build on the model of Jeong et al. (2012).

According to Jeong et al. (2012), a variable $x_t$ is not a significant predictor of another variable $y_t$ in the $\theta$-quantile of the lag vector $\{y_{t-1}, \ldots, y_{t-p}, x_{t-1}, \ldots, x_{t-p}\}$ if:

$$Q_\theta\{y_t | y_{t-1}, \ldots, y_{t-p}, x_{t-1}, \ldots, x_{t-p}\} = Q_\theta\{y_t | y_{t-1}, \ldots, y_{t-p}\} \tag{9}$$

$x_t$ is also not a significant predictor of $y_t$ in the $\theta$ th quantile of $\{y_{t-1}, \ldots, y_{t-p}, x_{t-1}, \ldots, x_{t-p}\}$ if:

$$Q_\theta\{y_t | y_{t-1}, \ldots, y_{t-p}, x_{t-1}, \ldots, x_{t-p}\} \neq Q_\theta\{y_t | y_{t-1}, \ldots, y_{t-p}\}, \tag{10}$$

where $Q_\theta\{y_t|\bullet\}$ is the $\theta$ th quantile of $y_t$. The conditional quantiles of $Q_\theta\{y_t|\bullet\}$ mainly depend on $t$, and maintain values ranging between 0 and 1 (i.e. $0 < \theta < 1$). Suppose that $Y_{t-1} \equiv (y_{t-1}, \ldots, y_{t-p})$, $X_{t-1} \equiv (x_{t-1}, \ldots, x_{t-p})$ and $Z_t = (X_t, Y_t)$, the functional forms of the conditional distribution of $y_t$ become $F_{y_t|Z_{t-1}}(y_t, Z_{t-1})$ and $F_{y_t|Y_{t-1}}(y_t, Y_{t-1})$, given $Z_{t-1}$ and $Y_{t-1}$, respectively. Suppose further that $Q_\theta(Z_{t-1}) \equiv Q_\theta(y_t|Z_{t-1})$ and $Q_\theta(Y_{t-1}) \equiv Q_\theta(y_t|Y_{t-1})$, then $F_{y_t|Y_{t-1}}\{Q_\theta(Z_t)|Z_{t-1}\} = \theta$ with the probability value being one (1). The null and alternative hypotheses of the quantiles-based test are thus given by:

$$H_0 = P\left\{F_{y_t|Y_{t-1}}\{Q_\theta(Z_t)|Z_{t-1}\} = \theta\right\} = 1 \tag{11a}$$

$$H_1 = P\left\{F_{y_t|Y_{t-1}}\{Q_\theta(Z_t)|Z_{t-1}\} = \theta\right\} < 1\ . \tag{11b}$$

Jeong et al. (2012) additionally employ the distance measure $J = \{\varepsilon_t E(Z_{t-1}) f_z(Z_{t-1})\}$, such that $\varepsilon_t$ and $f_z(Z_{t-1})$ respectively stand for the regression error and the marginal density function of $Z_{t-1}$. $\varepsilon_t$ is computed as:

$$\widehat{\varepsilon}_t = 1\{y_t \le \widehat{Q}_\theta(Y_{t-1})\} - \theta, \tag{12}$$

where $\widehat{Q}_\theta(Y_{t-1})$ denotes the estimator of the quantiles of $y_t$, given $y_{t-1}$,. $\widehat{Q}_\theta(Y_{t-1})$ is then estimated using the non-parametric kernel method:

$$\widehat{Q}_\theta(Y_{t-1}) = \widehat{F}^{-1}_{y_t|Y_{t-1}}(\theta y_{t-1}), \tag{13}$$

where $\widehat{F}^{-1}_{y_t|Y_{t-1}}(y_t y_{t-1})$ is the Nadarya-Watson kernel estimator, given as:

$$\widehat{F}^{-1}_{y_t|Y_{t-1}}(y_t y_{t-1}) = \frac{\sum_{s=p+1, s\neq t}^{T} L\Big((y_{t-1} y_{t-s} - R)/h\Big) 1(y_s \le y_t)}{\sum_{s=p+1, s\neq t}^{T} L\Big((y_{t-1} y_{t-s})/h\Big)}\ . \tag{14}$$

$L(\bullet)$ and $h$ respectively denote the kernel function and bandwidth.

Balcilar et al. (2016, 2017) further propose causality in higher order while relying on the approach of Nishiyama et al. (2011). The initial assumption is specified as:

$$y_t = r(Y_{t-1}) + \varpi(X_{t-1}) v_t, \tag{15}$$

where $r(\bullet)$ and $\varpi(\bullet)$ indicate the unknown functions under the condition of stationarity. The $Y_{t-1} \equiv (y_{t-1}, \ldots, y_{t-p})$, $X_{t-1} \equiv (x_{t-1}, \ldots, x_{t-p})$ are vectors defined to appropriately present the causality-in-quantiles test. $v_t$ is the disturbance term. With this specification, the Granger-causality test running from $X_{t-1}$ *to* $y_t$ is not allowed. Nonetheless, the "predictive power" from $X_{t-1}$ to $y_t^2$ given that $\varpi(\bullet)$ is a general nonlinear function can be obtained (Balcilar et al., 2016, 2017). Accordingly, the null and alternative hypotheses of the causal nexus at second order moment are specified as follows since $Z_t = (X_t, Y_t)$:

$$H_0 = P\left\{F_{y_t^2|Z_{t-1}}\{Q_\sigma(Y_{t-1}|Z_{t-1})\} = \theta\right\} = 1, \tag{16a}$$

$$H_1 = P\left\{F_{y_t^2|Z_{t-1}}\{Q_\sigma(Y_{t-1}|Z_{t-1})\} = \theta\right\} < 1\ . \tag{16b}$$

Generalizing the causality for higher order moments, it can be interpreted using:

$$y_t = r(Y_{t-1}, X_{t-1}) + v_t, \tag{17}$$

under the below null and alternative hypotheses generalized for the higher order quantiles-based causality:

$$H_0 = P\left\{F_{y_t^k|Z_{t-1}}\{Q_\sigma(Y_{t-1}|Z_{t-1})\} = \theta\right\} = 1, for\ k = 1, 2, \ldots, K, \tag{18a}$$

$$H_1 = P\left\{F_{y_t^k|Z_{t-1}}\{Q_\sigma(Y_{t-1}|Z_{t-1})\} = \theta\right\} < 1, for\ k = 1, 2, \ldots, K \tag{18b}$$

We test that $y_t$ granger causes $z_t$ in the $\sigma th$ quantile up to the $k$-$th$ moment through the use of equation (18a) to construct the test statistic of the equation of first moment (null hypothesis) for each $k$ and this is subsequently extended to a higher value of $k$. Owing to this, we check for the existence of causality-in-mean and variance successively. In all, the empirical implementation of causality testing via quantiles entails specifying the bandwidth $h$, the lag order $p$, and the kernel type for $K\ (\bullet)$ *and* $L\ (\bullet)$. In this present study, a lag of order one is used based on the Schwarz Information Criterion (SIC) in the VAR model. The bandwidth value in this study is selected using the least squares cross-validation method, while Gaussian-type kernels are employed for $K\ (\bullet)$ *and* $L\ (\bullet)$.

### 3.3. Data

We obtain daily data for the U.S. S&P green bond price index and 17 different predictors which are ten commodity prices (aluminum, coal, copper, cotton, crude oil, gold, natural gas, platinum, silver and wheat), four financial asset prices (U.S. S&P 500 stocks, the U.S. S&P 500 bond index, the Dow Jones Islamic Market World Index and the U.S. exchange rate), and three speculative factors (the economic policy uncertainty (EPU) index, investor sentiment and the CBOE volatility index (VIX)). As discussed earlier in the introduction, the green bond market is closely associated with a complex network of factors, including policy, economic and financial indicators (Anh Tu et al., 2020). This is essentially because the aim of the green bond market is to address climate change through the mitigation of carbon emissions, which also have multiple causes. Moreover, the contagion and risk transmission effects that often result in shock spillovers among financial markets further link the performance of the green bond market to other financial and commodity market indicators. These form the bedrock of the selected variables in the predictability framework for the performance of the green bond market in this study.

All the commodity prices are obtained from investing.com, while EPU, VIX and the U.S. exchange rate are sourced from the Federal Reserve database. The remaining data are sourced from Datastream. Based on data availability, the data range varies for some of the series. The range, as well as the 50% and 75% sub-samples for both the in-sample and out-of-sample analyses are presented in Table 1.

Briefly, we discuss the descriptive statistics of the data (the results are presented in the Appendix). Table A1 shows that all the assets, except coal, cotton, natural gas and platinum, have positive returns on average, with the highest recorded by the conventional (U.S. S&P 500) stocks (0.042%). Only VIX has a negative value among the speculative factors. The variability measure of the factors, captured through the standard deviation test, indicates that they are all highly volatile. Crude oil is the most volatile among the asset classes while EPU exhibits the highest degree of volatility among the speculative factors. They also show significant evidence of excess kurtosis, implying the likelihood of extreme shocks. However, they vary between positive and negative skewness. However, they are not normally distributed as established by the Jarque-Bera test. The ADF test also shows that they are all stationary as expected of returns series. Table A2 gives evidence of the presence of serial correlation and heteroskedasticity regardless of the lags used. Significant evidence of persistence is additionally revealed for the predictors, while endogeneity seems not to be inherent except for coal. This implies that endogeneity tends not to create a problem in the predictability. However, the presence of heteroskedasticity, serial correlation and persistence justify the need to consider a model that is consistent with them.

## 4. Empirical results

The empirical discussion is two-fold. The first is concerned with the results of the estimated predictive model of Westerlund and Narayan (2015). In this case, the predictability and forecast performance of commodities on the green bonds are considered for both the in-sample and out-of-sample analyses. The analysis is also extended to account for asymmetries. The other phase of this section is based on the results of the nonparametric causality-in-quantiles test where the predictive power of commodities on green bonds is examined for different market conditions.

### 4.1. Results from Westerlund and Narayan (2015) model

#### 4.1.1. Predictability results

We start with the predictability test results in order to show whether the commodity price returns are good predictors of the future commodity price returns. By definition, a variable is said to be a viable predictor of another if the estimate of its first-order autoregressive component is found to be statistically significant in the estimated predictive model (Adekoya, 2021), premised on the null hypothesis of no predictability. As seen in Table 2, the results of the symmetric predictive model show that the coefficients of majority

**Table 1**
Data description.

| Variables | | Start date | End date | Total obs. | In-sample obs. | | Out-sample obs. | | | | | |
|---|---|---|---|---|---|---|---|---|---|---|---|---|
| | | | | | 50% | 75% | 50% | | | 75% | | |
| | | | | | | | h = 60 | h = 120 | h = 180 | h = 60 | h = 120 | h = 180 |
| Green bond | | 12/1/08 | 9/23/20 | 3083 | 1542 | 2312 | 1602 | 1662 | 1722 | 2372 | 2432 | 2492 |
| Commodity series | Aluminum | 11/22/16 | 9/23/20 | 1002 | 501 | 752 | 561 | 621 | 681 | 812 | 872 | 932 |
| | Coal | 2/23/11 | 9/23/20 | 2373 | 1187 | 1780 | 1247 | 1307 | 1367 | 1840 | 1900 | 1960 |
| | Copper | 12/1/08 | 9/23/20 | 3083 | 1542 | 2312 | 1602 | 1662 | 1722 | 2372 | 2432 | 2492 |
| | Cotton | 10/15/09 | 9/23/20 | 2855 | 1428 | 2141 | 1488 | 1548 | 1608 | 2201 | 2261 | 2321 |
| | Crude oil | 12/1/08 | 9/23/20 | 3083 | 1542 | 2312 | 1602 | 1662 | 1722 | 2372 | 2432 | 2492 |
| | Gold | 12/1/08 | 9/23/20 | 3083 | 1542 | 2312 | 1602 | 1662 | 1722 | 2372 | 2432 | 2492 |
| | Natural gas | 12/1/08 | 9/23/20 | 3083 | 1542 | 2312 | 1602 | 1662 | 1722 | 2372 | 2432 | 2492 |
| | Platinum | 10/15/09 | 9/23/20 | 2855 | 1428 | 2141 | 1488 | 1548 | 1608 | 2201 | 2261 | 2321 |
| | Silver | 12/1/08 | 9/23/20 | 3083 | 1542 | 2312 | 1602 | 1662 | 1722 | 2372 | 2432 | 2492 |
| | Wheat | 12/1/08 | 9/23/20 | 3083 | 1542 | 2312 | 1602 | 1662 | 1722 | 2372 | 2432 | 2492 |
| Financial series | Conventional stock | 12/1/08 | 9/23/20 | 3083 | 1542 | 2312 | 1602 | 1662 | 1722 | 2372 | 2432 | 2492 |
| | Conventional bond | 12/1/08 | 8/28/20 | 3066 | 1533 | 2300 | 1593 | 1653 | 1713 | 2360 | 2420 | 2480 |
| | Islamic stock | 12/1/08 | 8/28/20 | 3066 | 1533 | 2300 | 1593 | 1653 | 1713 | 2360 | 2420 | 2480 |
| | US dollar | 12/1/08 | 9/23/20 | 3083 | 1542 | 2312 | 1602 | 1662 | 1722 | 2372 | 2432 | 2492 |
| Uncertainty | EPU | 12/1/08 | 9/23/20 | 3083 | 1542 | 2312 | 1602 | 1662 | 1722 | 2372 | 2432 | 2492 |
| | Investors sentiment | 12/1/08 | 8/14/20 | 3055 | 1528 | 2291 | 1588 | 1648 | 1708 | 2351 | 2411 | 2471 |
| | VIX | 12/1/08 | 9/23/20 | 3083 | 1542 | 2312 | 1602 | 1662 | 1722 | 2372 | 2432 | 2492 |

**Table 2**
Predictability test results.

| Predictors | Symmetry | | Asymmetry | | | |
|---|---|---|---|---|---|---|
| | 50% | 75% | 50% | | 75% | |
| | | | Positive | Negative | Positive | Negative |
| Aluminum | 0.0225** | 0.0134 | −0.0007 | 0.0169 | 0.0124 | 0.0147 |
| | (0.0096) | (0.0086) | (0.0323 | (0.0396) | (0.0107) | (0.0130) |
| Coal | −0.0173 | −0.0074 | −0.0365** | 0.0035 | −0.0167 | 0.0047 |
| | (0.0126) | (0.0096) | (0.0175) | (0.0163) | (0.0132) | (0.0124) |
| Copper | 0.1477*** | 0.1069*** | 0.1446*** | 0.1510*** | 0.1024*** | 0.1119*** |
| | (0.0094) | (0.0075) | (0.0124) | (0.0122) | (0.0099) | (0.0099) |
| Cotton | 0.0485*** | 0.0407*** | 0.0579*** | 0.0413*** | 0.0475*** | 0.0340*** |
| | (0.0083) | (0.0067) | (0.0124) | (0.0100) | (0.0098) | (0.0081) |
| Crude oil | 0.1123*** | 0.0439*** | 0.1078*** | 0.1152*** | 0.0378*** | 0.0498*** |
| | (0.0088) | (0.0051) | (0.0124) | (0.0102) | (0.0065) | (0.0065) |
| Gold | 0.1085*** | 0.0923*** | 0.1046*** | 0.1221*** | 0.1025*** | 0.1256*** |
| | (0.0070) | (0.0059) | (0.0132) | (0.0084) | (0.0086) | (0.0073) |
| Natural gas | 0.0046 | 0.0057 | 0.0082 | 0.0082 | 0.0072 | 0.0045 |
| | (0.0057) | (0.0041) | (0.0071) | (0.0071) | (0.0054) | (0.0052) |
| Platinum | 0.1701*** | 0.1433*** | 0.1599*** | 0.1767*** | 0.1421*** | 0.1442*** |
| | (0.0098) | (0.0073) | (0.0152) | (0.0120) | (0.0106) | (0.0092) |
| Silver | 0.1038*** | 0.0903*** | 0.1032*** | 0.1044*** | 0.0852*** | 0.0953*** |
| | (0.0057) | (0.0047) | (0.0085) | (0.0073) | (0.0066) | (0.0059) |
| Wheat | 0.0464*** | 0.0305*** | 0.0487*** | 0.0439*** | 0.0297*** | 0.0314*** |
| | (0.0069) | (0.0056) | (0.0087) | (0.0091) | (0.0068) | (0.0077) |
| Conventional stock | 0.2433*** | 0.1420*** | 0.2368*** | 0.2553*** | 0.1300*** | 0.1574*** |
| | (0.0145) | (0.0115) | (0.0196) | (0.0165) | (0.0160) | (0.0135) |
| Conventional bond | 0.3874*** | 0.5407*** | 0.3482*** | 0.4355*** | 0.4742*** | 0.6033*** |
| | (0.0509) | (0.0357) | (0.0715) | (0.0606) | (0.0498) | (0.0435) |
| Islamic stock | −0.0454** | −0.0328** | −0.0663*** | −0.0217 | 0.0046 | −0.0165 |
| | (0.0180) | (0.0142) | (0.0227) | (0.0237) | (0.0151) | (0.0155) |
| US dollar | −0.7936*** | −0.7012*** | −0.7704*** | −0.8214*** | −0.6998*** | −0.7031*** |
| | (0.0198) | (0.0135) | (0.0250) | (0.0269) | (0.0176) | (0.0173) |
| EPU | −0.00002 | −0.0001 | −0.0002 | 0.00007 | −0.0002 | −0.00004 |
| | (0.0003) | (0.0003) | (0.0004) | (0.0004) | (0.0003) | (0.0003) |
| Investors sentiment | −0.0010 | 0.0001 | 0.0013 | −0.0034 | 0.0015 | −0.0012 |
| | (0.0022) | (0.0016) | (0.0029) | (0.0034) | (0.0024) | (0.0022) |
| VIX | −0.0209*** | −0.0078*** | −0.0215*** | −0.0199*** | −0.0069*** | −0.0075*** |
| | (0.0019) | (0.0013) | (0.0022) | (0.0027) | (0.0017) | (0.0019) |

*** and ** indicate significance at 1% and 5% critical levels respectively.

of the predictors are significant under both 50% and 75% sub-samples. The implication of this is that the null hypothesis of no predictability is resoundingly rejected, so that a conclusion of strong predictive power of the predictors is made. The few exceptions where predictability cannot be established regardless of the sub-samples are coal, natural gas, EPU and investors' sentiments. To a very large extent, the results of the asymmetric predictive model complement those of the symmetric predictive model. However, it advances them by preliminarily showing that it is important to account for asymmetries in the models as the coefficients of both the positive and negative returns of the predictors are observed to be significant in most cases.

In addition to the statistical significance of the estimates, their signs provide some salient information. The coefficients of the speculative factors are clearly negatively signed in most cases. This aligns with expectations, justified by the fact that any of policy uncertainty, sentiments or market volatility has the tendency of discouraging individual and corporate investors from embarking on new investments, including green projects (Converse, 2017). In addition, these factors are probable inducers of the global financial cycle following their influence on global credits and asset price movements. The consequence is risk transmissions (Adekoya & Oliyide, 2020), making it possible for the considered global speculative factors to adversely affect the green bond returns. This evidence aligns with previous studies that find that policy uncertainty and VIX have a negative impact on financial market performance (Bouri et al., 2018; Mensi et al., 2014; You et al., 2017). However, it contradicts the positive response of green bond performance to investor sentiment. This can be hedged on the different measure of sentiment used. On the other hand, the coefficients of the commodity and financial assets vary between positive and negative, although they are mostly positive. This is also not unexpected since, theoretically, the returns of two assets can be negatively or positively related depending on whether there is a possibility of hedging between them (Adekoya et al., 2020). This evidence is thus in line with the recent finding of Naeem, Adekoya, and Oliyide (2021) that green bonds respond asymmetrically to commodities, and that of Piñeiro-Chousa et al. (2021) that stocks and green bonds are negatively related. Whatever the case is, the significance established in most cases give a green light to further carrying out the forecast evaluation analysis, particularly comparing the forecast performance of the asymmetric commodity-based and symmetric commodity-based predictive models.

#### 4.1.2. Forecast evaluation results

The forecast evaluation is carried out using the Campbell and Thompson (2008) test. The test compares two nested or competing models, with a positive value indicating that the unrestricted model outperforms the restricted model. If, on the other hand, the C-T value is negative, then the restricted model beats the unrestricted model.

In the literature, the conventional or baseline method for forecasting future asset returns is the historical average model which leaves out any exogenous factors in the forecast performance. However, the complexity of modern financial markets and the high degree of market integration is such that the historical average model provides inaccurate forecast evaluation results in the presence of other influencing factors. Therefore, we start by comparing the forecast performance of the historical average and factor-based predictive models. For clarity, the forecast performance of both the symmetric and asymmetric factor-based predictive models is distinctly compared with that of the historical average predictive model.

Table 3 presents the forecast evaluation results for the comparison between the symmetric factor-based (unrestricted) and historical average (restricted) predictive models. Both the in-sample and out-of-sample analyses are also conducted. For the 50% sample size, it is observed that the C-T statistics are positive for all the predictors, except conventional bond, implying that the predictive models of these factors beat the historical average model in forecasting the green bonds returns. The results are consistent for the in-sample and all the forecast horizons of the out-of-sample analyses. We further judge the sensitivity of the results to a higher sample size (i.e. 75%) in line with conventional practice in the literature (see Adekoya, 2021; Adekoya et al., 2022; Salisu & Isah, 2018). The 75% sub-sample results soundly corroborate those of the 50% sub-sample without any exception. These results position us well to conclude that financial markets are becoming more integrated with or dependent on other markets than on their own past information. This is revealed from our results where past price information of green bonds has a lower forecast power for the assets' returns compared to the exogenous predictors. A couple of studies (see, for instance, Adekoya, Ogunbowale et al., 2021; Fasanya & Adekoya, 2022) align with this evidence.

Then, we proceed to the forecast evaluation comparison between the asymmetric factor-based (unrestricted) predictive model and the historical average (restricted) model. Again, the C-T statistics are positive in all cases, for conventional bonds (see Table 4), leading to a similar conclusion as above. By and large, the factor-based predictive models offer a more accurate forecast of the green bonds returns than the historical average model, whether or not the former incorporates asymmetries in each factor.

Having shown that the factor-based predictive models offer the best forecast performance over the baseline (historical average) model, we now determine if asymmetries matter in the forecast analysis. This involves comparing the symmetric and asymmetric factor-based predictive models. In this case, the former is the restricted model while the latter is the unrestricted model. Table 5 indicates that, for the 50% sub-sample, the asymmetric factor-based predictive model outperforms the symmetric factor-based predictive model in forecasting green bond returns for most of the factors except copper, crude oil, natural gas, silver, conventional stock, conventional bond and VIX where asymmetries do not matter. Turning to the 75% sub-sample results, we find similar evidence for most of the predictors, although some are sensitive to different samples. For instance, the asymmetric predictive models for silver and the conventional stocks now perform better than their symmetric models in forecasting green bond returns. On the other hand, the symmetric predictive models of Islamic stock and the U.S. exchange rate do better than their asymmetric variants. Nonetheless, the asymmetric model is still found superior in most cases.

In a more intuitive language, the fact that the asymmetric predictive models outperform the symmetric predictive models in most cases suggests that positive and negative changes in the prices of the predictors can provide a better forecast of the future returns of green bonds than the actual price series. In other words, leaving out asymmetric changes in the predictors tends to undermine accurate forecasting of green bond returns. When this occurs, it becomes difficult for green investors to have an accurate prediction of the

**Table 3**
C-T test results for symmetric vs. historical average predictive models.

| Predictors | 50% of the data sample | | | | 75% of the data sample | | | |
|---|---|---|---|---|---|---|---|---|
| | In-sample RMSE | Out-sample RMSE | | | In-sample RMSE | Out-sample RMSE | | |
| | | h = 60 | h = 120 | h = 180 | | h = 60 | h = 120 | h = 180 |
| Aluminum | 0.0036 | 0.0049 | 0.0049 | 0.0043 | 0.0032 | 0.0032 | 0.0018 | 0.0038 |
| Coal | 0.0007 | 0.0005 | 0.0004 | 0.0005 | 0.0003 | 0.0003 | 0.0003 | 0.0002 |
| Copper | 0.1041 | 0.1015 | 0.0994 | 0.0984 | 0.0727 | 0.0721 | 0.0720 | 0.0719 |
| Cotton | 0.0242 | 0.0241 | 0.0229 | 0.0229 | 0.0179 | 0.0175 | 0.0178 | 0.0181 |
| Crude oil | 0.0571 | 0.0540 | 0.0525 | 0.0513 | 0.0277 | 0.0275 | 0.0275 | 0.0274 |
| Gold | 0.0332 | 0.0290 | 0.0289 | 0.0282 | 0.0272 | 0.0270 | 0.0269 | 0.0271 |
| Natural gas | 0.0053 | 0.0053 | 0.0053 | 0.0053 | 0.0050 | 0.0050 | 0.0050 | 0.0050 |
| Platinum | 0.0892 | 0.0882 | 0.0831 | 0.0814 | 0.0745 | 0.0746 | 0.0752 | 0.0754 |
| Silver | 0.0715 | 0.06980 | 0.0702 | 0.0707 | 0.0613 | 0.0610 | 0.0608 | 0.0608 |
| Wheat | 0.0257 | 0.0251 | 0.0251 | 0.0248 | 0.0182 | 0.0182 | 0.0179 | 0.0177 |
| Conventional stock | 0.0910 | 0.0877 | 0.0864 | 0.0843 | 0.0508 | 0.0504 | 0.0498 | 0.0496 |
| Conventional bond | −0.0015 | −0.0011 | −0.0007 | −0.0006 | −0.0039 | −0.0036 | −0.0034 | −0.0002 |
| Islamic stock | 0.0021 | 0.0021 | 0.0023 | 0.0021 | 0.0026 | 0.0026 | 0.0026 | 0.0026 |
| US dollar | 0.2145 | 0.2148 | 0.2176 | 0.2197 | 0.2178 | 0.2178 | 0.2178 | 0.2180 |
| EPU | 0.0043 | 0.0043 | 0.0043 | 0.0043 | 0.0037 | 0.0037 | 0.0037 | 0.0037 |
| Investors sentiment | 0.0038 | 0.0038 | 0.0038 | 0.0038 | 0.0039 | 0.0039 | 0.0039 | 0.0039 |
| VIX | 0.0360 | 0.0361 | 0.0337 | 0.0325 | 0.0134 | 0.0133 | 0.0132 | 0.0132 |

**Table 4**
C-T test results for asymmetric vs. historical average predictive models.

| Predictors | 50% of the data sample | | | | 75% of the data sample | | | |
|---|---|---|---|---|---|---|---|---|
| | In-sample RMSE | Out-sample RMSE | | | In-sample RMSE | Out-sample RMSE | | |
| | | h = 60 | h = 120 | h = 180 | | h = 60 | h = 120 | h = 180 |
| Aluminum | 0.0059 | 0.0066 | 0.0057 | 0.0048 | 0.0033 | 0.0033 | 0.0020 | 0.0038 |
| Coal | 0.0013 | 0.0009 | 0.0006 | 0.0006 | 0.0005 | 0.0006 | 0.0005 | 0.0005 |
| Copper | 0.1037 | 0.1012 | 0.0992 | 0.0981 | 0.0725 | 0.0719 | 0.0717 | 0.0715 |
| Cotton | 0.0249 | 0.0246 | 0.0240 | 0.0238 | 0.0179 | 0.0175 | 0.0168 | 0.0170 |
| Crude oil | 0.0569 | 0.0537 | 0.0521 | 0.0509 | 0.0276 | 0.0274 | 0.0274 | 0.0273 |
| Gold | 0.0301 | 0.0301 | 0.0302 | 0.0299 | 0.0308 | 0.0307 | 0.0308 | 0.0311 |
| Natural gas | 0.0053 | 0.0052 | 0.0051 | 0.0052 | 0.0050 | 0.0050 | 0.0049 | 0.0049 |
| Platinum | 0.0893 | 0.0885 | 0.0832 | 0.0814 | 0.0746 | 0.0747 | 0.0753 | 0.0745 |
| Silver | 0.0710 | 0.0694 | 0.0697 | 0.0703 | 0.0617 | 0.0613 | 0.0612 | 0.0612 |
| Wheat | 0.0001 | 0.0001 | 0.0001 | 0.00001 | 0.0181 | 0.0180 | 0.0178 | 0.0176 |
| Conventional stock | 0.0906 | 0.0873 | 0.0861 | 0.0842 | 0.0510 | 0.0506 | 0.0500 | 0.0498 |
| Conventional bond | −0.0021 | −0.0002 | −0.0011 | −0.0009 | −0.0041 | −0.0039 | −0.0037 | −0.0032 |
| Islamic stock | 0.0030 | 0.0031 | 0.0031 | 0.0030 | 0.0026 | 0.0026 | 0.0026 | 0.0026 |
| US dollar | 0.2155 | 0.2160 | 0.2187 | 0.2207 | 0.2175 | 0.2176 | 0.2172 | 0.2178 |
| EPU | 0.0045 | 0.0045 | 0.0045 | 0.0044 | 0.0037 | 0.0037 | 0.0037 | 0.0037 |
| Investors sentiment | 0.0049 | 0.0047 | 0.0046 | 0.0046 | 0.0044 | 0.0044 | 0.0043 | 0.0043 |
| VIX | 0.0360 | 0.0341 | 0.0337 | 0.0325 | 0.0131 | 0.0130 | 0.0129 | 0.0131 |

**Table 5**
C-T test results for asymmetric vs. symmetric predictive model using RMSE.

| Predictors | 50% of the data sample | | | | 75% of the data sample | | | |
|---|---|---|---|---|---|---|---|---|
| | In-sample RMSE | Out-of-sample RMSE | | | In-sample RMSE | Out-of sample RMSE | | |
| | | h = 60 | h = 120 | h = 180 | | h = 60 | h = 120 | h = 180 |
| Aluminum | 0.0023 | 0.0017 | 0.0008 | 0.0005 | 0.0001 | 0.0001 | 0.0002 | 0.0001 |
| Coal | 0.0006 | 0.0004 | 0.0002 | 0.0001 | 0.0002 | 0.0002 | 0.0002 | 0.0002 |
| **Copper** | **−0.0005** | **−0.0004** | **−0.0003** | **−0.0003** | **−0.0002** | **−0.0003** | **−0.0003** | **−0.0003** |
| Cotton | 0.0007 | 0.0006 | 0.0011 | 0.0009 | 0.0006 | 0.0004 | 0.0002 | 0.0001 |
| **Crude oil** | **−0.0002** | **−0.0003** | **−0.0004** | **−0.0004** | **−0.0001** | **−0.0001** | **−0.0001** | **−0.0001** |
| Gold | 0.00004 | 0.0012 | 0.0014 | 0.0018 | 0.0037 | 0.0038 | 0.0040 | 0.0042 |
| **Natural gas** | **0.00003** | **−0.0001** | **−0.0002** | **−0.0002** | **−0.0001** | **−0.00004** | **−0.00004** | **−0.0001** |
| Platinum | 0.0002 | 0.0003 | 0.0001 | 0.0001 | 0.00004 | 0.00005 | 0.00006 | 0.00004 |
| **Silver** | **−0.0004** | **−0.0004** | **−0.0004** | **−0.0004** | 0.0004 | 0.0004 | 0.0004 | 0.0004 |
| Wheat | 0.0001 | 0.0001 | 0.0001 | 0.00001 | **−0.0001** | **−0.0001** | **−0.0001** | **−0.0001** |
| **Conventional stock** | **−0.0004** | **−0.0005** | **−0.0003** | **−0.0002** | 0.0002 | 0.0002 | 0.0002 | 0.0003 |
| **Conventional bond** | **−0.0006** | **−0.0005** | **−0.0003** | **−0.0004** | **−0.0002** | **−0.0002** | **−0.0003** | **−0.0002** |
| Islamic stock | 0.0009 | 0.0009 | 0.0009 | 0.0008 | **−0.00002** | **−0.00003** | **−0,00003** | **−0.00004** |
| US dollar | 0.0014 | 0.0014 | 0.0015 | 0.0011 | **−0.0003** | **−0.0003** | **−0.0003** | **−0.0003** |
| EPU | 0.0002 | 0.0002 | 0.0002 | 0.0002 | 0.00002 | 0.00003 | 0.00002 | 0.00003 |
| Investors sentiment | 0.0010 | 0.0009 | 0.0008 | 0.0008 | 0.0005 | 0.0005 | 0.0004 | 0.0004 |
| **VIX** | **−0.0001** | **−0.00002** | **−0.00002** | **0.00004** | **−0.0003** | **−0.0003** | **−0.0003** | **−0.0003** |

Footnote: Values in bold indicates that asymmetric factor-based predictive model do not outperform the symmetric factor-based predictive model in forecasting green bonds returns.

performance of their green bonds especially in the face of recurring turbulences that cause the movements of the commodity and financial asset prices to fluctuate and dictate unstable government economic policies. We are not surprised to have these results given the complexity of the contemporary commodity and financial markets and the policies of the government as a result of diverse endogenous and exogenous shocks. These events create asymmetries in asset price dynamics and policy uncertainties. Within the context of financial asset returns forecast, Adekoya (2021) and Fasanya et al. (2022) also show that the role of asymmetries in the predictors cannot be relegated.

### *4.2. Nonparametric causality-in-quantiles test results*

The second phase of this analysis examines if green bond returns can be predicted by commodities, financial assets and speculative factors across different quantiles, which represent different market conditions. Since the nonparametric causality-in-quantiles test is a measure of a nonlinear relationship, it is important to first pre-test the series for the possible existence of nonlinearity. We do this with the aid of the BDS test developed by Brock et al. (1996). The test uniquely detects the presence of nonlinearities, yet not influenced by any linear dependencies in the data. The results are presented in Table 6 where it is observed that the null hypothesis of independent and identical distribution is resoundingly rejected at the 1% significance level across all the chosen lags. This evidence is in line with

**Table 6**
BDS test results.

| Causal variables | 2 | 3 | 4 | 5 | 6 |
|---|---|---|---|---|---|
| Aluminum | 0.0138*** | 0.0272*** | 0.0341*** | 0.0373*** | 0.0381*** |
| Coal | 0.0175*** | 0.0363*** | 0.0531*** | 0.0647*** | 0.0705*** |
| Copper | 0.0333*** | 0.0634*** | 0.0867*** | 0.1023*** | 0.1107*** |
| Cotton | 0.0187*** | 0.0393*** | 0.0560*** | 0.0687*** | 0.0758*** |
| Crude oil | 0.0330*** | 0.0629*** | 0.0860*** | 0.1015*** | 0.1098*** |
| Gold | 0.0332*** | 0.0633*** | 0.0867*** | 0.1024*** | 0.1108*** |
| Natural gas | 0.0333*** | 0.0634*** | 0.0868*** | 0.1022*** | 0.1104*** |
| Platinum | 0.0182*** | 0.0387*** | 0.0549*** | 0.0681*** | 0.0754*** |
| Silver | 0.0328*** | 0.0626*** | 0.0855*** | 0.1008*** | 0.1091*** |
| Wheat | 0.0326*** | 0.0623*** | 0.0851*** | 0.1006*** | 0.1088*** |
| Conventional Stock | 0.0315*** | 0.0605*** | 0.0831*** | 0.0979*** | 0.1054*** |
| Conventional bond | 0.0326*** | 0.0628*** | 0.0866*** | 0.1024*** | 0.1110*** |
| Islamic stock | 0.0331*** | 0.0633*** | 0.0868*** | 0.1024*** | 0.1108*** |
| US Dollar | 0.0322*** | 0.0626*** | 0.0857*** | 0.1017*** | 0.1101*** |
| EPU | 0.0332*** | 0.0633*** | 0.0867*** | 0.1023*** | 0.1107*** |
| Investors Sentiment | 0.0333*** | 0.0635*** | 0.0870*** | 0.1025*** | 0.1108*** |
| VIX | 0.0328*** | 0.0622*** | 0.0849*** | 0.1000*** | 0.1078*** |

the informal evidence provided under the preliminary analysis that the series exhibit excess kurtosis sub-optimal skewness as a fair support to the presence of nonlinearity in the series. As such, we are justified to put the causality-in-quantiles test into use.

Figs. 1–3 present the results. The role of the considered factors cannot be jettisoned in the predictability of the performance of the green bond market as their trend lines rise above the significance line in virtually all cases. All the commodities profoundly affect the green bond returns across all the quantiles (Fig. 1). Only coal tends to have no significant impact on the performance of the green bond somewhere around a few middle quantiles. Nonetheless, significance is established for it in other quantiles. Similar evidence is observed for the financial assets which are all found to be significant predictors of green bond returns (Fig. 2). Intuitively, the commodity and conventional financial markets have significant impacts on the green bond market at different market conditions. Whether

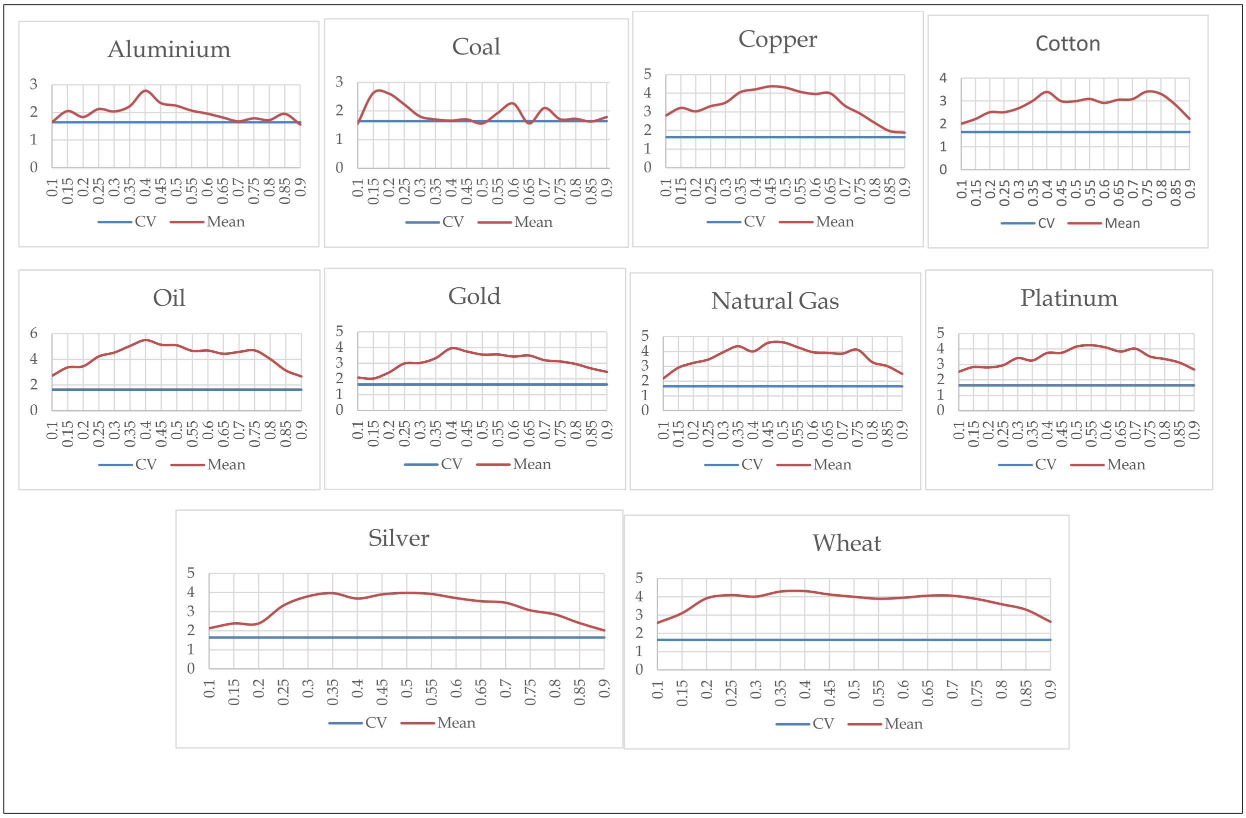


**Fig. 1.** Commodity series and Green bond. (For interpretation of the references to colour in this figure legend, the reader is referred to the Web version of this article.)

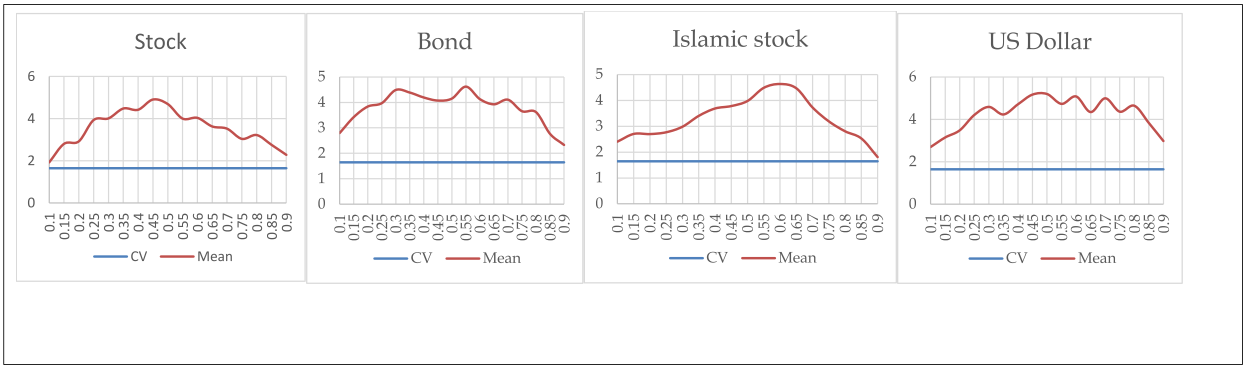


**Fig. 2.** Financial series and green bond. (For interpretation of the references to colour in this figure legend, the reader is referred to the Web version of this article.)

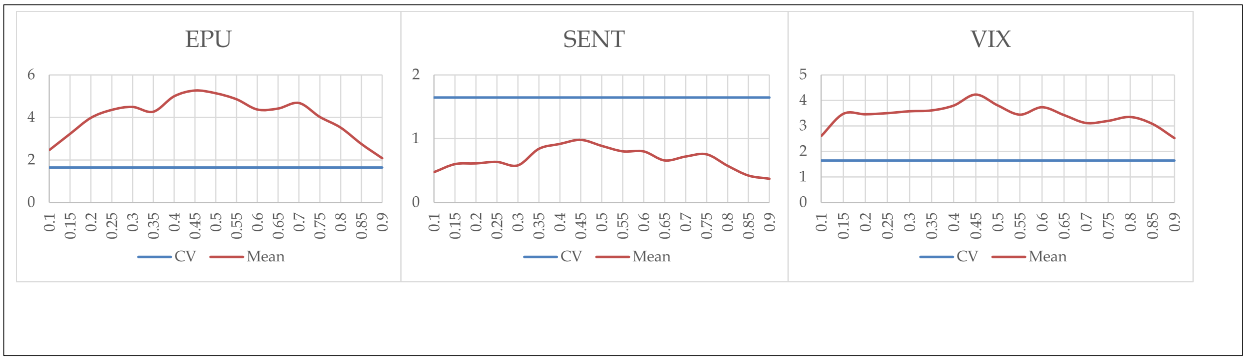


**Fig. 3.** Uncertainties and green bond. (For interpretation of the references to colour in this figure legend, the reader is referred to the Web version of this article.)

or not the market is normally behaved or is at the extreme (i.e., bearish or bullish), the commodity market plays a significant role in determining the performance of the green bond market. The predictive role of most of these indicators on green bonds across all the quantiles mirrors the findings of Yan et al. (2022) that the considered commodity and stock prices affect the predictability of the performance of the green bond market.

For the speculative factors, only EPU and VIX strongly affect green bond returns, while investor sentiment has no effect across all the quantiles. This suggests the fact that the green bond market tends to be more sensitive to institutional and overall market-based uncertainty than the perceived sentiments of individuals. Besides, the predictive influence of both EPU and VIX also cuts across all the market states. We find similar evidence to that found by Pham and Nguyen (2022) which demonstrates the significant role of uncertainty indices in influencing green bond returns, although they include a caveat that the magnitude and persistence of the connection varies across market states.

## 5. Conclusion

Over the past few years, the green bond market has significantly progressed and responded well to the intended goal of using it as a means of raising funds for environmentally friendly projects in order to address the global concern of climate change. However, in the face of market buoyancy and with regard to its future viability it is important to determine the factors which are able to predict its performance. Accordingly, many studies have responded to the call to examine the connection of the green bond market with different factors, but these studies have not been comprehensive enough, while there is little or no evidence regarding the forecast performance of the considered indicators on the performance of the green bond market.

Addressing the inherent gaps in the literature, the first objective of this study is to predict and forecast green bond returns with different classes of assets and speculative factors. The robust classes of predictors used serve as the second contribution of this study. We consider ten commodity assets (covering energy, precious metals, industrial metals and agriculture), four financial assets (covering bonds, stocks and exchange rates) and three speculative factors (namely EPU, investor sentiment and VIX), making up 17 indicators in all. This is perhaps the most robust study on the connection of the green bond market with other indicators. More importantly, the nexus between green bonds and speculative factors has enjoyed less empirical attention. Third, we use a novel methodology proposed by Westerlund and Narayan (2015) owing to its intrinsic worth and then account for asymmetries. Finally, the predictive power of the predictors on green bond returns are considered across different market conditions through the novel non-parametric causality-in-quantiles test.

We find that virtually all the factors considered are strong predictors of green bond returns, and the consideration of asymmetries matters in the relationship. The coefficients are largely negative for the speculative factors, but mixed for the commodity and financial assets. Against this evidence, we set out to perform the forecast analysis, with the results showing that both the symmetric and asymmetric factor-based predictive models outperform the baseline (historical) average model in providing an accurate forecast of green bond returns. In order to then determine the role of asymmetries in the forecast performance, the forecasting power of both the factor-based symmetric and asymmetric predictive models is considered. The results are mixed, although the asymmetric model offers a more accurate forecast performance in most cases. Finally, the causality-in-quantiles test reveals that all the commodities impose a strong causal impact on green bond returns across all the quantiles, except coal around some of the middle quantiles. Without any exception, all the financial assets significantly affect green bond returns across all the quantiles. In the case of the speculative factors, investor sentiment is the only indicator that fails to significantly affect green bond returns across all the quantiles.

These results have a number of relevant policy implications for portfolio investors and policy makers. For investors, the presence of no/a weak or a negative relationship between green bond returns and some of the commodity and financial assets such as aluminum, coal, Islamic stocks and the U.S. exchange rate suggests that the green bonds present the possibility of portfolio diversification. Thus, adding green bonds to the investment portfolio will create a hedging advantage and mitigate losses. However, investors need to watch the overall stock market volatility (measured by VIX) as it tends to adversely affect the performance of the green bond market. On the other hand, policy makers must not jettison the predictive power of the predictors when implementing policies associated with the green bond market. The strong connection between the green bond market and the predictors suggests that events in the commodity and financial markets, as well as the behavior of the speculative factors can exert an impact on the viability of the performance of the green bond market either positively or negatively, depending on the nature of the effect. As such, policy measures taken on the green bond market without due consideration of these predictors can neutralize the effectiveness of the policies. Moreover, the absence of a significant predictive nexus between investor sentiment and green bond returns passes a message to the policy makers that they should be more concerned with institutional and overall market-based uncertainty than the individually-based sentiments. In addition, as it is true that the green bond market is still maturing compared to other financial markets, it is essential for policy makers to strategize on how to enhance its stability given its vulnerability to policy uncertainties and events in other financial and commodity markets. Only when green investors can be assured of reasonable returns will they be motivated to invest in green bonds. As such, deliberate policy actions, such as green bond investment subsidies, regular organization of campaigns and public awareness programs on the importance of investment in green projects towards the mitigation of environmental degradation and climate change, reduced taxes on green bonds returns, and encouragement of divestment from commodity assets (especially fossil fuels), should be implemented by the government.

Since the literature on green bonds is still emerging with several stylized facts yet to be established in the literature, future work should address other issues such as the presence of cyclical patterns and volatility persistence in green bond returns using fractional integration approaches (Abakah, Caporale, & Gil-Alana, 2021; Gil-Alana et al., 2020; Abakah, Gil-Alana, Madigu, & Romero-Rojo, 2020), and also employ alternative methods such as Johansen's (2012) FCVAR, and Markov-switching copula (Abakah, 2021; Tiwari, Abakah, Adekoya, & Hammoudeh, 2021) to investigate further price connectedness between green bonds and other asset classes.

**Table A1**
Descriptive statistics and unit root

| | Mean | Maximum | Minimum | Std. Dev. | Skewness | Kurtosis | Jarque-Bera | ADF |
|---|---|---|---|---|---|---|---|---|
| **Green bond** | 0.003 | 6.815 | −3.782 | 0.532 | 0.943 | 21.924 | 46459.49*** | −33.07*** |
| **Aluminum** | 0.000 | 5.975 | −7.910 | 1.178 | 0.059 | 6.685 | 567.5141*** | −33.56*** |
| **Coal** | −0.031 | 7.817 | −11.463 | 1.169 | −0.137 | 14.389 | 12831.67*** | −29.48*** |
| **Copper** | 0.020 | 8.689 | −7.717 | 1.517 | 0.106 | 6.416 | 1504.659*** | −58.95*** |
| **Cotton** | −0.001 | 7.784 | −12.348 | 1.557 | −0.307 | 6.454 | 1464.233*** | −50.24*** |
| **Crude oil** | 0.009 | 31.963 | −28.221 | 2.744 | 0.295 | 27.340 | 76146.2*** | −54.86*** |
| **Gold** | 0.027 | 11.969 | −11.797 | 1.543 | −0.060 | 17.748 | 27941.3*** | −33.07*** |
| **Natural gas** | −0.036 | 26.771 | −18.055 | 3.035 | 0.629 | 8.072 | 3507.103*** | −59.01*** |
| **Platinum** | −0.018 | 9.931 | −13.614 | 1.356 | −0.637 | 12.705 | 11396*** | −49.95*** |
| **Silver** | 0.027 | 12.196 | −19.546 | 2.122 | −0.573 | 9.007 | 4804.563*** | −60.20*** |
| **Wheat** | 0.000 | 11.607 | −11.715 | 1.926 | 0.241 | 6.232 | 1372.033*** | −57.41*** |
| **Conventional stock** | 0.042 | 9.345 | −10.955 | 1.167 | −0.894 | 16.144 | 22602.33*** | −64.31*** |
| **Conventional bond** | 0.010 | 2.051 | −2.854 | 0.287 | −0.804 | 14.657 | 17683.62*** | −27.42*** |
| **Islamic stock** | 0.033 | 5.199 | −7.047 | 0.851 | −0.498 | 9.113 | 4899.644*** | −50.36*** |
| **US dollar** | 0.003 | 2.233 | −2.745 | 0.482 | −0.006 | 4.965 | 496.1426*** | −55.24*** |
| **EPU** | 0.025 | 321.561 | −314.833 | 48.814 | 0.060 | 5.341 | 699.347*** | −22.521*** |
| **Investors sentiment** | 0.005 | 67.871 | −64.288 | 6.609 | −0.241 | 25.493 | 64432.18*** | −20.458*** |
| **VIX** | −0.0300 | 76.825 | −35.060 | 7.583 | 1.172 | 10.015 | 6963.094*** | −60.195*** |

*** represents significance at 1%.

**Table A2**
Serial correlation, heteroskedasticity and endogeneity tests results.

| variables | Q-stat | | | $Q^2$-stat | | | ARCH-LM | | | Persistence | Endogeneity |
|---|---|---|---|---|---|---|---|---|---|---|---|
| | m = 10 | m = 20 | m = 30 | m = 10 | m = 20 | m = 30 | m = 10 | m = 20 | m = 30 | | |
| Green bond | 56.208*** | 75.395*** | 106.94*** | 1191.8*** | 1665.4*** | 2237.2*** | 68.89*** | 46.05*** | 33.40*** | ___ | ___ |
| Aluminum | 18.995** | 49.265*** | 64.705*** | 441.81*** | 464.38*** | 468.17*** | 27.04*** | 15.23*** | 10.19*** | −0.06** | −0.005 |
| Coal | 66.481*** | 76.173*** | 86.640*** | 138.79*** | 158.84*** | 191.33*** | 10.91*** | 6.43*** | 5.14*** | 0.10** | 0.012* |
| Copper | 19.556** | 35.692** | 77.401*** | 1215.0*** | 2117.2*** | 2990.8*** | 49.73*** | 32.34*** | 22.34*** | −0.06*** | 0.0002 |
| Cotton | 21.026** | 41.815*** | 57.754*** | 373.18*** | 573.35*** | 792.91*** | 19.44*** | 11.09*** | 8.55*** | 0.06*** | 0.0007 |
| Crude oil | 26.953*** | 73.642*** | 101.33*** | 1562.1*** | 2187.2*** | 2767.6*** | 92.95*** | 56.24*** | 43.96*** | 0.01*** | 0.001 |
| Gold | 264.35*** | 294.04*** | 347.35*** | 612.38*** | 663.51*** | 716.12**** | 92.16*** | 48.16*** | 32.86*** | −0.27*** | 0.008 |
| Natural gas | 30.018*** | 46.409*** | 65.729*** | 323.78*** | 482.49*** | 655.06*** | 19.99*** | 11.73*** | 10.41*** | −0.06*** | 0.0001 |
| Platinum | 29.159*** | 58.405*** | 90.961*** | 906.78*** | 1026.0*** | 1172.3*** | 68.17*** | 40.22*** | 28.09*** | 0.06*** | 0.00007 |
| Silver | 27.868*** | 38.578*** | 49.002*** | 238.54*** | 275.33*** | 310.08*** | 21.54*** | 11.75*** | 8.73*** | −0.07*** | 0.003 |
| Wheat | 19.315*** | 30.293** | 44.036** | 281.99*** | 363.63*** | 453.35*** | 17.20*** | 9.17*** | 7.21*** | −0.03*** | 0.002 |
| Conventional stock | 129.16** | 156.02*** | 173.55*** | 2844.7*** | 3373.4 | 3477.5*** | 154.71*** | 84.48*** | 57.42*** | −0.13*** | 0.008 |
| Conventional bond | 82.688*** | 96.807*** | 109.96*** | 2364.3*** | 2658.0*** | 2677.9*** | 142.27*** | 78.30*** | 55.94*** | 0.09*** | −0.009 |
| Islamic stock | 51.448*** | 65.871*** | 87.894*** | 776.29*** | 1223.5*** | 1669.7*** | 50.94*** | 29.39*** | 22.20*** | 0.10*** | 0.008 |
| US dollar | 12.047*** | 18.181*** | 23.046*** | 416.18*** | 596.42*** | 795.36*** | 22.83*** | 11.93*** | 9.07*** | 0.004 | −0.0007 |
| EPU | 513.14*** | 533.96*** | 577.01*** | 262.66*** | 328.42*** | 334.44*** | 28.146*** | 16.487*** | 11.180*** | −0.398*** | −0.089 |
| Investors sentiment | 264.99*** | 289.54*** | 300.08*** | 1191.8*** | 1665.4*** | 2237.2*** | 59.094*** | 31.916*** | 24.417*** | −0.0000 | 0.003 |
| VIX | 38.953*** | 49.791*** | 57.439*** | 254.48*** | 259.12*** | 264.31*** | 17.809*** | 9.034*** | 6.147*** | −0.080*** | −0.025 |

## Data availability

Data will be made available on request.

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