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Do oil shocks affect the green bond market?

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ABSTRACT

This study examines the predictive power of oil shocks for the green bond markets. In line with this aim, we investigated the extent to which oil shocks could be used to accurately make in- and out-of-sample forecasts for green bond returns. Three striking findings emanated from our results: First, the three types of oil shock are reliable predictors for green bond indices. Second, the performances of the predictive models were consistent across the different forecasting horizons (i.e. H = 1 to H = 24). Third, our findings were sensitive to classifying the dataset into pre-COVID and COVID eras. For instance, the results confirmed that the predictive power of oil shocks declined during the crisis period. We also discuss some policy implications of this study's findings.

1. Introduction

Growing concerns over climate change have shifted the attention of policymakers and investors towards environmentally friendly investments. Consequently, the global issuance of green investment bonds reached the substantial milestone of a trillion US dollars in 2020, and it is further anticipated to reach $5 trillion annually by 2025. This means accelerating capital allocation for sustainable agriculture, clean energy, green transport, resilient infrastructure, and so on across 62 developed and emerging economies. However, investment in green bonds in particular has gained significant prominence since its introduction in 2007 by the European Investment Bank (EIB) as part of the transition to become more climate-resilient. Since 2015, green bond issuance has grown considerably from $46.1 billion to $354.2 billion in 2021, which was around 37% higher than in 2020. For instance, according to Sustainable Bond Insight (2021), the European financial market is the leading player with a 48.72% stake in the global issuance of green bonds, followed by the United States with 35.3%, Japan with 3.41%, the United Kingdom with 3.03%, Sweden with 2.02%, Switzerland with 0.45%, Norway with 0.36%, and New Zealand with 0.34%. These countries collectively issue around 93% of the world's green bonds. This tremendous growth in green bond issuance is accompanied by an increasing popularity among investors. For example, according to a survey by the Climate Bond Initiative (2021), market sentiment for green bonds is strengthening, and the green investment trend is set to accelerate, with it likely reaching the $1 trillion milestone by end of 2022.[1] Similarly, a survey by Morgan Stanley (2016) found that 55% of investors were interested in sustainable investments, with 31% of investors viewing it as a virtuous investment approach for the future.

Kilian (2009) identified oil demand and supply shocks using structural VAR on the data of oil shipping prices and production representing oil demand and supply, respectively. Later, Kilian and Park (2009) extended this work by examining the effect of different shocks on US equity market. Their results highlight low variation in equity returns (not greater than 2%) driven by the residuals in oil prices which are neither related to supply nor associated with the aggregate demand of oil. However, this framework inherent a weakness that the data used in SVAR is required to have correlation with the contemporaneous or future oil price changes in order to identify shocks. For example, according to Kilian (2009), the identified demand and supply shocks explain only 4% contemporaneous variations in oil prices from 1986 to 2011. Remaining variations in oil prices are explained as 19% by the SVAR whereas 77% by the residuals as classified by the precautionary demand shocks. However, there is no way to determine if changes in the precautionary demand shocks are due to expectations of changes in demand or by the concerns over supply. For instance, escalating oil

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[1] These statistics are sourced from https://www.climatebonds.net/

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prices due to an increasing probability of supply constraint which never happens will not be recognized by the VAR. Similarly, increasing oil prices due to increase in demand which is not mirrored in high shipping prices will not be reflected. Both these changes are recognized as precautionary demand shocks although they would have different implications for economic output and aggregate equity returns.

This limitation therefore, required an identification technique relying upon the forward looking prices of traded assets to avoid such issues. Ready (2018) define demand shocks as portion of the contemporaneous returns of a global index of oil producing companies which are orthogonal to the unexpected changes in log values of VIX which is considered as a proxy of aggregate changes in discount rates of market, driven by the changing attitude towards risk. Supply shocks are estimated as the portion of contemporaneous changes in oil prices which are orthogonal to demand shocks along with innovations in VIX. The innovations to VIX (proxy to risk shocks), supply shocks and demand shocks tend to be orthogonal and account for all variations in oil prices. This extension by Ready (2018) resulted in almost entire variations in the oil prices are captured by supply shocks (78%) and demand shocks (21%) due to very low correlation of VIX with the oil prices.

Since there is limited literature about the connection between oil shocks and green bonds, it is not clear if oil shocks trigger changes in the GBM and therefore carry useful information for predicting future returns in the GBM. Thus, examining the consequences of oil shocks (i.e. demand, supply, and risk shocks) to predict green bond returns is important for helping investors to assess the risk and return behaviour of the green bonds market. The goal of this paper is therefore to investigate the predictability of green bond returns using oil shocks, which were extracted using the methodology proposed by Ready (2018). Hence, we aimed to answer the following questions: First, can oil shocks, based on international oil prices, predict green bond returns? Second, how does this predictability vary across different sample markets, given that international oil shocks may have different impacts on the green bonds of different countries? Finally, does the predictability vary between the normal and COVID-19 crisis periods? These testable questions, if answered, should help investors in understanding the behaviour of the GBM in the presence of oil shocks, since the effect that the international oil market has on the world economy is undeniable. With such knowledge, investors will be able to better balance their portfolios of green bonds from different countries. Our results highlight the significant predictability of green bond returns based on oil market shocks. Both Japanese and US green bond returns are more accurately forecasted, irrespective of investment horizon (i.e. H_1 to H_{24}). On the contrary, a supply shock is not effective for forecasting both in- and out-of-sample returns for New Zealand's GBM, whereas it can be used to accurately predict returns for green bonds in Denmark, Europe, Japan, Norway, Sweden, Switzerland, the UK, and the US. However, during the COVID-19 crisis period, supply shock weakly forecasts only the in-sample, extremely long-term (i.e. 24 months) returns of Swedish green bonds, and it fails to forecast the short- and medium-term returns (i.e. less than a month to less than 12 months). In contrast, supply shocks only forecast the in-sample returns for Switzerland's green bond during the COVID-19 pandemic. The CW statistics highlight that oil shocks do not accurately forecast both the in- and out-of-sample returns that are specific to Danish and European GBMs during the COVID-19 period.

The remainder of this paper is presented as follows: Section 2 explains the estimation techniques, while Section 3 discusses the data source and preliminary results. Section 4 then explains our findings before Section 5 finally concludes our work.

2. Literature review

Investment in the green bond markets (GBMs) has grown in both scope and size over recent years, with it showing signs of co-movement with other general asset classes (Pham and Huynh, 2020) and the energy market (Reboredo, 2018) in particular. For instance, Lee et al. (2021) employed causality in quantiles and reported significant bidirectional causality from the oil market to the MSCI green bond index at lower quantiles, indicating that the oil and green bond markets jointly influence each other. In contrast, Dutta et al. (2020) argued that negative (positive) variations in the oil market cause a decrease (increase) in the incentives for green investment. In other work, Pham and Nguyen (2021) reported that the connection between oil market uncertainty and green bonds is both state-dependent and time-varying. More specifically, throughout periods of low (high) uncertainty, the oil and green bond markets are weakly (strongly) linked, indicating that green bonds can be used to hedge against uncertainty in the oil market. A weak connection between the green bond and oil markets was also documented by Braga et al. (2021), who stated that S&P Green Bonds are less affected by variations in oil prices, which means there are hedging and diversification opportunities for investors. Similarly, Ferrer et al. (2021), meanwhile, found that the behaviour of the GBM is virtually unaffected by developments in oil prices. Dutta et al. (2021) also reported similar results in that they found climate bonds to weakly correlate with crude oil prices, with the hedge ratio switching between positive and negative states for the climate bond and oil pairing, particularly during the COVID-19 pandemic, indicating reduced risk reduction during the pandemic. More recently, Kanamura (2021) examined the relationships that S&P green bond indices, MSCI, and Solactive have with the oil market and reported that S&P green bonds and MSCI were positively associated with oil prices, whereas Solactive green bond prices showed a negative correlation with oil prices, similar to the traditional S&P bond index.

The oil market has always received major attention as an economic indicator, thus highlighting the strong linkage of oil prices with other traded assets (i.e. commodities) (Chen and Rehman, 2021; Mensi et al., 2021), foreign currencies (Liu et al., 2020), Logistic industry (Maitra et al., 2021) and bonds (Kang et al., 2014). However, oil prices have experienced significant fluctuations over the past decades. For example, oil prices reached an all-time high in June 2008 of $140.5 per barrel, but that was followed by a decline of around 70% in January 2009 to $40.1 per barrel. A second major decline in oil prices was observed in June 2014, when they fell from $105.2 per barrel to $33.6 per barrel by January 2016. The most recent decrease in oil prices started in December 2019 and lasted until April 2020, resulting in another 67% decline in oil prices (i.e. from $60.1 to $20.1 per barrel). However, each decline in oil prices is followed by a boom, indicating a significant increase in the demand for oil in the market. Excessive oil demand or supply can result in changes in oil prices, and these can be classified as demand shocks (i.e. demand driven) or supply shocks (i.e. supply driven). We follow the example of Ready (2018) in examining whether oil shocks are instigated by excessive demand or insufficient supply and whether these two different shocks have a similar impact on green bond returns because an increase in the oil spot prices due to lower oil supply or higher oil demand may result in different shocks to the oil market (Kilian, 2008; Güntner, 2014).

According to Henriques and Sadorsky (2008), oil price shocks do not have any significant effect on the returns of alternative energy stocks. However, on the contrary Kumar et al. (2012) report the presence of positive relationship between oil and alternative energy prices. According to Sadorsky (2012), stocks of clean energy firms are less correlated with the oil market. In terms of relationship between oil and clean energy stocks, Managi and Okimoto (2013) examine and report positive impact on clean energy stocks following structural breaks in 2007. In one of the comprehensive work on oil prices and South American countries, Apergis and Payne (2015) report that real oil prices have a positive effect on the consumption of renewable energy for eleven south American countries. Later, Reboredo et al. (2017) find weak relationship between the returns of renewable energy stock and oil in the short-run which however strengthens in the long-run. During the long-run period, increasing oil prices provides incentives to the renewable energy projects whereas decrease in oil prices negatively affects renewable energy companies. In one of the work examining relationship between oil and US market, Reboredo and Ugolini (2018) find that changes in the prices of new energy stocks in US are mostly attributable to oil prices changes. These findings are supported by Shah et al. (2018) that oil price shocks have a positive effect on investments in renewable energy in the US and Norway whereas little and negative effect in the UK.

According to Kocaarslan and Soytas (2019), fluctuations in dollar affects the correlation between oil and clean energy prices. Likewise, Pham (2019) record heterogeneous responses of oil prices on clean energy stocks however, such effects depends on the energy sectors. Another work by Kyritsis and Serletis (2019) highlight that the renewable energy stocks exhibit resistance to uncertainty in oil prices. On the contrary, Dutta et al. (2020) find that oil market volatility has a significant effect on green assets more than the fluctuations in prices of oil. In terms of diversification between oil and green bonds, Kanamura (2020) examines dynamic correlation between the prices of green bonds and oil and reports the presence of positive correlation between these two assets. However, disaggregating oil prices into supply and demand driven shocks, Zhao (2020) reports positive effect of oil supply shocks whereas negative effect of oil demand shocks on clean energy stock returns.

Another recent work which examines the connectedness of green bonds market with oil shocks include Azhgaliyeva et al. (2022). The authors in this work use flow crude oil supply, flow crude oil demand and speculative demand shocks to examine their impact on the issuance of corporate green bonds. They report that though the issuance of corporate green bonds is positively affected by the oil flow supply and demand shocks, the impact by these shocks on the issuance of corporate green bonds is not significant.

3. Methodology

3.1. The model

As mentioned earlier, the aim of this study is to investigate the predictive potential of oil shocks for green bond returns. As such, we specify our predictive model in the form:

$$r_t = \alpha + \beta s_{t-1} + \varepsilon_t, \tag{1}$$

where *r* represents the return on green bonds, calculated as log (kt/kt-1), and *K* is the green bonds index, both at the aggregate and disaggregated level, while *s* is the measure of oil shocks. Thus, Eq. (1) expresses a typical predictive model. Studies have shown that high frequency data can be susceptible to statistical problems, such as conditional heteroscedasticity, persistence, and endogeneity effects (Salisu et al., 2019; Isah and Raheem, 2019), and these can hinder the use of OLS models. However, Westerlund and Narayan (2015), hereinafter referred to as WN, proposed that accounting for these features requires re-specifying Eq. (1) as follows:

$$r_t = \alpha + \beta_1 s_{t-1} + \beta_2 (s_t - \gamma s_{t-1}) + \varepsilon_t, \tag{2}$$

where the first term ($\beta_1 s_{t-1}$) represents first order autocorrelation, while the second term, $\beta_2(s_t - \gamma s_{t-1})$, captures the persistence effect and the resulting endogeneity incorporated in the parameter. In order to test for persistence, Eq. (3) is estimated using OLS:

$$s_t = \alpha + \beta s_{t-1} + \mu_t, \text{ where } \mu_t \sim N(0, \sigma_v^2) \tag{3}$$

Similarly, the conditional heteroscedasticity effect can be tested using the ARCH-LM test. WN argued that rather than using OLS, the feasible quasi-generalized least squares (FQGLS) technique is better because it has the ability to extract any information embedded in the conditional heteroscedasticity effect. FQGLS is based on the assumption that the error term in Eq. (1) pursues an autoregressive conditional heteroskedastic (ARCH) structure of $\widehat{\sigma}^2_{\varepsilon,t} = \varphi + \sum_{i=1}^{q} \varphi_i \widehat{\varepsilon}^2_{t-1}$, such that the resulting $\widehat{\sigma}^2_{\varepsilon,t}$ can be used to weigh the predictive model. (See the work of Salisu et al., 2019 for detailed computational descriptions.)

In this study, we go beyond using a bivariate predictive model to account for some important control variables, so we expanded Eq. (2) to measure oil shocks. The resulting equation takes the form:

$$r_t = \alpha + \beta_1 s_{t-1} + \beta_2 (s_t - \gamma s_{t-1}) + \beta_3 U_t + \varepsilon_t, \tag{4}$$

where *U* is the measure for oil shocks.

3.2. Forecast implementation and evaluation

The model is based on both in- and out-of-sample predictions. The out-of-sample prediction is structured for short- and long-run horizons. Although there is no conventional rule for dichotomizing the data over two periods (i.e. in and out of the sample), we follow the existing literature in using 50% and 75%. The out-of-sample forecasting horizons are H = 1 (1 month), 3 (3 months), 6 (6 months), 12 (12 months), and 24 (24 months).

Model 1 is called a restricted model, and this is also the benchmark model. For completeness, two forms of the benchmark model are specified, namely autoregressive and historical average. Model 2 is an unrestricted model. The forecasting evaluation is based on three different measures, the test of Campbell and Thompson (2008), hereinafter referred to as the CT test; Theil's U statistic; and the test of Clark and West (2007), hereinafter referred to as the CW test. The literature (Narayan and Gupta, 2015) reveals that Theil's U statistic is calculated as the ratio of forecasting error of the unrestricted model to that of the restricted model. A Theil's U with a value lower than unity implies that the unrestricted model has greater predictive power than the restricted model.

The out-of-sample R^2 (OOS_ R) statistic is considered in the CT test. It is computed as OOS_R = 1 - Theil's U statistic $\{(\widehat{RMSE}_2/\widehat{RMSE}_1)\}$. The $\widehat{RMSE}_2$ *and* $\widehat{RMSE}_1$ represent the root mean square error for models 2 and 1, respectively. A positive CT value indicates that model 2 outperforms model 1 and vice-versa for a negative value. However, a shortcoming of the CT test is its inability to demonstrate the significance level.[2] However, the CW test (Clark and West, 2007) allows checking the significance level of the CT value[3]:

In order to estimate the CW value, we used the following equation:

$$\widehat{f}_{t+k} = \left(S_{t+k} - \widehat{S}_{1t,t+k}\right)^2 - \left[\left(S_{t+k} - \widehat{S}_{2t,t+k}\right)^2 - \left(\widehat{S}_{1t,t+k} - \widehat{S}_{2t,t+k}\right)^2\right], \tag{5}$$

where the forecast period is denoted by k, and the squared error for the restricted model (i.e. model 1) is denoted by $\left(S_{t+k} - \widehat{S}_{1t,t+k}\right)^2$, while $\left(S_{t+k} - \widehat{S}_{2t,t+k}\right)^2$ is the squared error for the unrestricted model (i.e. model 2). Next, $\left(\widehat{S}_{1t,t+k} - \widehat{S}_{2t,t+k}\right)^2$ is the adjusted squared error due to the introduction of CW to correct for the noise associated with the larger model's forecast. Hence, the average of the sample $\widehat{f}_{t+k}$ is stated as $RMSE_1 - (RMSE_2 - adj.)$, where each term is calculated as follows:

$$RMSE_1 = P^{-1}\left(S_{t+k} - \widehat{S}_{1t+k}\right)^2;$$

$$RMSE_2 = P^{-1}\sum \left(S_{t+k} - \widehat{S}_{2t+k}\right)^2; \text{and}$$

[2] Because of the connection between Clark and West (2007) and Campbell and Thompson (2008) tests, as well as for better understanding, we do not present Campbell and Thompson (2008) test results. For instance, when the U statistic has a value less than 1, we mathematically expect that the Campbell and Thompson (2008) test would present a positive value and vice-versa.

[3] Diebold and Mariano (1995) test used to be the most commonly employed test until recently, despite it being suitable for nested models only, whereas the CW test provides better results for nested models.

$$\text{Adj.} = P^{-1}\sum\left(\widehat{S}_{1t+k} - \widehat{S}_{2t+k}\right)^2 \quad (6)$$

where the number of predictions used to calculate the averages is denoted by P.

The term $\widehat{f}_{t+k}$ is regressed on a constant, and the resulting t-statistic for a zero coefficient is used to draw inferences, so we can investigate the relative forecasting performances of models 1 and 2. We tested the null hypothesis (H0) against the alternative hypothesis based on whether the t-statistic for a one-sided 0.10 test or a one-sided 0.05 test is greater than $+1.286$ or $+\ 1.645$, respectively.

3.3. Constructing supply and demand shocks

We follow the example of Ready (2018) in building the oil demand and supply shocks. The orthogonal demand shocks d_t, supply shocks s_t, and risk shocks v_t are defined for primary analysis as:

$$X_t \equiv \begin{bmatrix} \Delta p_t \\ R_t^{Prod} \\ \xi_{VIX,t} \end{bmatrix}, Z_t \equiv \begin{bmatrix} s_t \\ d_t \\ v_t \end{bmatrix}, A \equiv \begin{bmatrix} 1 & 1 & 1 \\ 0 & a_{22} & a_{23} \\ 0 & 0 & a_{23} \end{bmatrix} \quad (7)$$

The detected shocks from the observable factors are mapped by the matrix A, such that:

$$X_t = AZ_t \quad (8)$$

To ensure orthogonality, a_{22}, a_{23}, a_{23} and σ_s, σ_d, σ_v satisfy:

$$A^{-1}\Sigma_X\left(A^{-1}\right)^T = \begin{bmatrix} \sigma_s^2 & 0 & 0 \\ 0 & \sigma_d^2 & 0 \\ 0 & 0 & \sigma_v^2 \end{bmatrix}, \quad (9)$$

where σ_s, σ_d and σ_v are the identified shocks' volatilities, while Σ_X is the covariance matrix of the observable X_t. This is simply a renormalization of the standard orthogonalization used to define the structural shocks in an SVAR setting. It should be noted that despite the volatility shocks being normalised to one, the shocks are constrained to sum up to the total change in the price of oil.

4. Data and preliminary analysis

Our work employed daily data for nine green bond indices in New Zealand, the United Kingdom, the United States, Switzerland, Norway, Europe, Denmark, Japan, and Sweden. The returns for all these indices were calculated by taking the natural log of the two adjacent pricing levels. To construct oil shocks, we followed the example of Ready (2018), who introduced an innovative technique for classifying changes in oil prices as being supply-driven (i.e. supply shocks) or demand-driven (i.e. demand shocks). We defined supply shocks as changes in the oil price that are orthogonal to the contemporaneous returns of oil-producing firms, with the forecasted values being categorized as "oil demand shocks". To construct the series for oil supply and demand shocks, we used three variables, namely an index of oil-producing companies, a measure of oil price changes, and a proxy for changes in expected returns. For the oil-producing companies, we used the World Integrated Oil and Gas Producer Index, which comprises large, publically traded oil-producing companies that represent the majority of the global oil industry. Next, the one-month returns on the second-nearest maturity NYMEX Light Sweet Crude Oil contract were used to identify unexpected changes to oil prices. Innovations to the VIX index were used to proxy changes in the discount rate. We calculated the VIX index from the options date, so it provides a measure of the risk-neutral expectation of volatility. The variance risk premium estimated from the VIX index definitely predicts stock returns, indicating that it may be a reasonable proxy for changes in risk, as suggested by Bollerslev et al. (2009). In order to segregate unexpected changes in the VIX, we estimated the ARMA(1,1), while the residuals from this process were used as innovations ξ_{VIX}.

Data for all the green bond indices, oil prices, the World Integrated Oil and Gas Producer Index (WIOGPI), and West Texas Intermediate (WTI) index for the period from December 2, 2008 to July 11, 2021 were obtained from the Thomson Reuters Datastream.

Table 1 presents the descriptive statistics for the nine green bond indices and the extracted oil shocks. Panel A of Table 1, meanwhile, highlights that all green bond indices, other than Switzerland, provided positive average daily returns. The highest average daily returns of 0.009% were earned by the European green bonds, followed by the Japanese and Norwegian green bonds (0.008% each), whereas the lowest average daily returns of 0.003% were observed for the Swedish green bonds. The maximum variance among the green bond indices was seen for Japanese green bonds (0.69%), followed by the New Zealand (0.58%) and UK (0.56%) bonds, while both the Danish and European green bond indices both showed the lowest variance (i.e. standard deviation) of 0.35%. Panel B of Table 1 shows that only the supply shocks exhibit positive values, while risk shocks have a maximum variance of 7.51%. Table 1 also presents the stochastic features of our sampled series. We applied the Augmented Dickey-Fuller (ADF) unit root test to reject the null hypothesis of a unit root being present for all series. Panel C of Table 1 provides evidence of endogeneity in the oil supply, oil demand, and risk series. We also witnessed the existence of serial dependence and conditional heteroscedasticity, regardless of the selected lag order, so the results validate the decision to use the generalized adjusted OLS for predicting green bond returns.

5. Analysis and discussion

We started our estimations by using a bias-adjusted measure of oil shocks for a single factor model, as shown in Table 2. Overall, we found evidence of predictability, irrespective of the nature of oil shocks (i.e. whether they were due to demand, supply, or risk) for all green bonds other than the UK's green bonds. Demand shocks predict all green bond returns, whereas supply shocks only explain variation in the returns of green bonds in Europe, Switzerland, Norway, Denmark, Sweden, New Zealand, Japan, and the US. The results are similar for the case of risk shocks, although the signs (directions) of the coefficients reveal a different story. The relationship between oil supply and demand (risk) shocks and the green bond returns for Denmark, Europe, Japan, Switzerland, and the US is positive (negative). Yet again, UK green bonds behave differently in that they are negatively associated only with demand shocks but positively associated with both supply and risk shocks. It is worth noting that when demand and supply shocks are negatively associated with green bond returns, the oil risk maintains a positive relationship with the same green bonds, and vice versa. In other words, the type of the oil shock (i.e. demand, supply, or risk) seems to be an important consideration when predicting green bonds returns. Overall, our results reveal an asymmetric relationship between oil shocks and green bond returns.

The results for in- and out-of-sample forecasting are presented in Tables 3–6. In particular, Tables 3 and 4 present forecasts with individual oil shocks for the full sample period (December 2, 2008 to July 11, 2021), whereas the latter tables (5–6) show the forecast for just the COVID-19 pandemic period (December 2, 2020 to July 11, 2021). We start by presenting the Theil's U statistics in Table 3, with these highlighting that the in-sample forecasts are very close for periods less than a month, and for few cases, horizons of less than three months. This holds regardless of the type of oil shock being considered. A Theil's U statistic value less than 1 indicates that oil shocks can accurately predict green bond returns. Table 3 presents further evidence for the significance of Theil's U for forecasting all green bonds based on oil shocks. More specifically, the Theil's U statistics are less than 1 for each case, regardless of the type of oil shock or investment horizon. Notably, we find that both the Japanese and US green bonds are more accurately

Table 1
Preliminary analysis.

	Mean	Std. Dev	Unit Root			
Stock Returns			Level	1st Diff		
Panel A: Descriptive Statistics						
Denmark GBs	0.00004	0.0035	−52.228***	–		
Euro GBs	0.00009	0.0035	−52.195***	–		
Japan GBs	0.00008	0.0069	−58.189***	–		
New Zealand GBs	0.00005	0.0058	−61.064***	–		
Norway GBs	0.00008	0.0054	−57.678***	–		
Sweden GBs	0.00003	0.0041	−59.084***	–		
Switzerland GBs	−0.00005	0.0055	−40.389***	–		
UK GBs	0.00005	0.0056	−54.696***	–		
US GBs	0.00004	0.0052	−57.398***	–		
Panel B: Oil Shock						
Supply shocks	0.0006	0.0272	−56.334***	–		
Demand shocks	−0.0007	0.0149	−19.822***	–		
Risk shocks	−0.0004	0.0751	−56.524***	–		
Panel C: Autocorrelation and Heteroscedasticity						
	Q-Stat		Q^2-Stat		ARCH-LM	
	K = 10	K = 20	K = 10	K = 20	K = 10	K = 20
Supply shocks	31.65***	51.029***	2022.0***	3043.6***	120.3***	76.96***
Demand shocks	81.15***	111.7***	1617.1***	2158.1***	114.1***	72.05***
Risk shocks	20.98***	32.64**	183.3***	186.5***	13.04***	6.606***

Table 2
Predictive model.

Indices	Demand shocks	Supply shocks	Risk shocks
Denmark GBs	0.0134***	0.0081***	−0.0028***
	(0.004)	(0.0023)	(0.0008)
Euro GBs	0.0136***	0.0079***	−0.0027***
	(0.0041)	(0.0023)	(0.0008)
Japan GBs	0.1730***	0.0574***	−0.0246***
	(0.0074)	(0.0043)	(0.0015)
New Zealand GBs	−0.0695***	−0.0194***	0.0093***
	(0.0067)	(0.0037)	(0.0013)
Norway GBs	−0.1295***	−0.0477***	0.0132***
	(0.0059)	(0.0034)	(0.0012)
Sweden GBs	−0.0695***	−0.0196***	0.0077***
	(0.0046)	(0.0026)	(0.0009)
Switzerland GBs	0.0654***	0.0219***	−0.0107***
	(0.0063)	(0.0036)	(0.0012)
UK GBs	−0.0123**	0.0016	0.0020
	(0.0065)	(0.0035)	(0.0013)
US GBs	0.1082***	0.0346***	−0.0087***
	(0.0057)	(0.0032)	(0.0012)

Note: ***, ** and * significance at 1, 5, and 10% respectively. Standard error values are in parenthesis.

predicted by all three shocks. The predictability of these bond markets is greatest under all horizons, right up to 24 months. We further note that the predictability is greater under short-term horizons, with the Theil's U increasing slightly as the horizon increases. Finally, when comparing between oil shocks, we find evidence to indicate that demand shocks are more effective for forecasting GBM returns for both in and out of the sample.

Next, we report the results for the pairwise measure of prediction performance evaluation in Table 4. The motivation for this analysis was the potential for extending the prediction model by again incorporating oil shocks into the estimation model. The CW test measures the level of statistical significance, with a value above 2.5 indicating statistical significance at the 5% level. Interestingly, the CW statistics are above 2.5 in most cases. In particular, both demand and risk shocks seem to be more accurate for forecasting the green bond returns of all sample indices, but the results differ for supply shocks. Supply shocks are the only factor that fails to predict both in- and out-of-sample returns for New Zealand's green bonds, while its predictive power is limited for the green bonds of Denmark, Europe, and the United Kingdom. In contrast, an evaluation based on supply shocks shows superior results when forecasting the returns of Japanese, Swedish, and American green bonds. In other words, the CW statistics are higher, indicating that supply shocks more accurately predict the returns of green bonds in Japan, Sweden, and the US, irrespective of the horizon. These findings resemble the results with demand and risk shocks, with these showing superior prediction for Japanese, Swedish, and American green bonds compared to those of Norway and the UK at both short- and long-term investment horizons. More specifically, the estimates for all green bonds are greater than the threshold of 2.5, and this persists for both demand shocks and risk shocks. This predictability is also more apparent in the case of Japanese and American green bonds. Overall, the CW statistics are higher for the Japanese GBM, irrespective of the kind of oil shock and investment horizon, indicating that oil shocks are more efficient for forecasting Japanese green bond returns at both short- and long-term investment horizons. Notably, this observation is not just specific to the CW model—it happens for the Theil's U model as well (see Table 3).

Next, we continued with our forecasting estimation for the sub-period covering the COVID-19 pandemic. Tables 5–6 present the predictive abilities of the Theil's U and CW forecasting models during distressed market conditions. The results from the Theil's U model highlight how oil market shocks can efficiently predict green bond returns both in and out of sample and for all investment horizons. A U statistic less than 1 indicates that oil shocks can predict GBM returns, so supply shocks predict all GBMs irrespective of investment horizon, with the exception of the UK GBM during the COVID-19 pandemic. However, the predictive power of supply shocks differs across investment horizons. In the short run, the U statistics are above the threshold of 1, indicating that supply shocks are inefficient for forecasting the UK's GBM under a short-term investment horizon (i.e. H = 1 and H = 3). In contrast, supply shocks present superior results when forecasting the returns of Japanese and Norwegian green bonds, suggesting that supply shocks can be used to forecast green bond returns during distressed market conditions. Likewise, using demand shocks to forecast green bond returns yields findings that resemble those when using supply shocks to forecast green bond returns. We can also see how demand shocks accurately predicted green bond returns during the COVID-19

Table 3
Single predictor: Theil's U-STATISTICS.

	Supply						Demand					
		Out- Sample						*Out- Sample*				
	In-S	H = 1	H = 3	H = 6	H = 12	H = 24	In-S	H = 1	H = 3	H = 6	H = 12	H = 24
Denmark GBs	0.9933	0.9934	0.9973	0.9946	0.9955	0.9960	0.9919	0.9919	0.9926	0.9932	0.9936	0.9944
Euro GBs	0.9932	0.9932	0.9936	0.9945	0.9954	0.9959	0.9920	0.9920	0.9928	0.9933	0.9937	0.9945
Japan GBs	0.9487	0.9489	0.9490	0.9505	0.9509	0.9527	0.8694	0.8693	0.8692	0.8701	0.8713	0.8722
New Zealand GBs	0.9987	0.9986	0.9986	0.9988	0.9990	0.9989	0.9842	0.9843	0.9845	0.9844	0.9844	0.9849
Norway GBs	0.9746	0.9746	0.9740	0.9753	0.9739	0.9741	0.9753	0.9742	0.9747	0.9733	0.9743	0.9746
Sweden GBs	0.9875	0.9856	0.9855	0.9867	0.9862	0.9881	0.9619	0.9621	0.9617	0.9655	0.9661	0.9676
Switzerland GBs	0.9851	0.9851	0.9854	0.9862	0.9872	0.9878	0.9701	0.9701	0.9707	0.9712	0.9717	0.9724
UK GBs	0.9899	0.9900	0.9903	0.9900	0.9908	0.9915	0.9854	0.9854	0.9855	0.9852	0.9858	0.9865
US GBs	0.9425	0.9428	0.9427	0.9432	0.9432	0.9447	0.8513	0.8513	0.8506	0.8516	0.8519	0.8535

	Risk					
		Out- Sample				
	In-S	H = 1	H = 3	H = 6	H = 12	H = 24
Denmark GBs	0.9902	0.9902	0.9908	0.9908	0.9907	0.9910
Euro GBs	0.9903	0.9903	0.9909	0.9909	0.9908	0.9910
Japan GBs	0.9376	0.9376	0.9375	0.9378	0.939	0.9408
New Zealand GBs	0.9907	0.9908	0.9907	0.9904	0.9903	0.9910
Norway GBs	0.9913	0.9912	0.9907	0.9915	0.9918	0.9920
Sweden GBs	0.9905	0.9906	0.9904	0.9915	0.9922	0.9927
Switzerland GBs	0.9793	0.9793	0.9798	0.9801	0.9798	0.9803
UK GBs	0.9965	0.9965	0.9965	0.9964	0.9967	0.9965
US GBs	0.9637	0.9636	0.9632	0.9636	0.9643	0.9661

Note: U-statistics less than 1 demonstrate that measures of oil shocks are reliable predictors of GBM returns.

Table 4
Single predictor: CW statistics.

	Supply						Demand					
		Out-Sample						*Out-Sample*				
	In-S	H = 1	H = 3	H = 6	H = 12	H = 24	In-S	H = 1	H = 3	H = 6	H = 12	H = 24
Denmark GBs	2.376	2.049	2.328	2.193	2.376	1.996	5.397	5.397	5.381	5.270	5.358	5.249
Euro GBs	2.388	2.388	2.342	2.207	2.063	2.008	5.340	5.341	5.202	5.226	5.319	5.339
Japan GBs	7.101	7.092	7.112	7.104	7.135	7.090	10.268	10.274	10.303	10.324	10.294	10.284
New Zealand GBs	1.135	1.075	1.172	1.163	1.141	1.094	5.415	5.448	5.499	5.647	5.702	5.505
Norway GBs	4.940	4.935	5.050	5.060	5.293	5.446	4.657	4.666	4.835	4.725	4.688	4.701
Sweden GBs	6.439	6.470	6.510	6.248	6.451	6.069	4.955	4.920	4.991	4.725	4.614	4.546
Switzerland GBs	4.737	4.524	4.701	4.642	4.741	4.470	7.702	7.699	7.637	7.606	7.716	7.703
UK GBs	2.208	2.206	2.183	2.240	2.192	2.146	3.215	3.220	3.248	3.316	3.194	3.047
US GBs	5.747	5.902	5.776	5.838	5.746	5.897	8.830	8.831	8.906	8.911	8.921	8.802

	Risk					
		Out-Sample				
	In-S	H = 1	H = 3	H = 6	H = 12	H = 24
Denmark GBs	3.398	3.398	3.241	3.152	3.095	2.946
Euro GBs	3.369	3.369	3.210	3.127	3.067	2.919
Japan GBs	11.512	11.518	11.561	11.583	11.586	11.611
New Zealand GBs	5.357	5.342	5.378	5.439	5.507	5.492
Norway GBs	6.190	6.192	6.343	6.201	6.383	6.541
Sweden GBs	9.509	9.490	9.573	9.055	9.151	9.100
Switzerland GBs	6.987	6.983	6.930	6.905	6.890	6.849
UK GBs	4.837	4.839	4.831	4.910	4.853	4.767
US GBs	11.70	11.701	11.775	11.819	11.889	11.909

Notes: CW measures the level of statistical significance. Values above 2.5 imply stat. Significance at 5%.

period. This prediction is more obvious for the Japanese and Norwegian green bonds at both in- and out-of-sample horizons, as well as for the US GBM at out-of-sample horizons. The out-of-sample findings are specific to short- and intermediate-term periods of up to 12 months, indicating that variations in oil shocks can forecast green bond returns during inefficient market conditions. Likewise, the risk-based model is also important for forecasting GBMs. Values of less than 1 show that risk shocks are a good predictor of green bond returns during the COVID-19 pandemic. When comparing between green bonds, we found that risk shocks are more crucial in providing accurate forecasts, because the Theil U's statistics are relatively lower in cases of the Japanese, New Zealand, and Norwegian green bond markets at both in- and out-of-sample investment horizons. Overall, we found that all three forecasting models are relatively efficient at forecasting the returns of Japanese and Norwegian GBMs during the COVID-19 period.

Table 6 presents some interesting results for the CW evaluation of forecasting performance during the COVID-19 pandemic. The CW-based estimation models also incorporate similar oil shocks as regressors. The CW test measures the level of statistical significance, such that a value above 2.5 indicates statistical significance at the 5% level. We highlight how the CW statistics clearly deviate from the findings based on Theil's U presented earlier in Table 5. More specifically, we can observe how

Table 5
Single predictor: Theil's U statistics (COVID-19).

	Supply						Demand					
		Out-Sample						*Out-Sample*				
	In-S	H = 1	H = 3	H = 6	H = 12	H = 24	In-S	H = 1	H = 3	H = 6	H = 12	H = 24
Denmark GBs	0.9890	0.9793	0.9806	0.9826	0.9840	0.9851	0.9954	0.9877	0.9881	0.9909	0.9928	0.9942
Euro GBs	0.9912	0.9931	0.9913	0.9915	0.9912	0.9911	0.9967	0.9918	0.9922	0.9923	0.991	0.9922
Japan GBs	0.9587	0.9570	0.9562	0.9510	0.9510	0.9539	0.9098	0.9042	0.9094	0.8932	0.8959	0.9030
New Zealand GBs	0.9931	0.9980	0.9982	0.9971	0.9962	0.9947	0.9500	0.9518	0.9541	0.9516	0.9545	0.9525
Norway GBs	0.9465	0.9414	0.9424	0.9428	0.9421	0.9436	0.8378	0.8086	0.8132	0.8174	0.8291	0.8315
Sweden GBs	0.9928	0.9963	0.9971	0.9943	0.9932	0.9931	0.9427	0.9263	0.9289	0.9276	0.9353	0.9377
Switzerland GBs	0.9953	0.9997	0.9991	0.9993	0.9994	0.9971	0.9733	0.9766	0.9756	0.9763	0.9770	0.9749
UK GBs	0.9973	1.0007	1.00008	0.9998	0.9994	0.9988	0.9766	0.9790	0.9783	0.9794	0.9783	0.9797
US GBs	0.9988	0.9981	0.9981	0.9980	0.9982	0.9982	0.9195	0.8747	0.8750	0.8817	0.8926	0.9008

	Risk					
		Out-Sample				
	In-S	H = 1	H = 3	H = 6	H = 12	H = 24
Denmark GBs	0.9930	0.9913	0.9910	0.9930	0.9940	0.9980
Euro GBs	0.9933	0.9930	0.9934	0.9932	0.9924	0.9934
Japan GBs	0.9568	0.9388	0.9396	0.9426	0.9444	0.9507
New Zealand GBs	0.9470	0.9461	0.9466	0.9468	0.9447	0.9431
Norway GBs	0.9389	0.9416	0.9412	0.9398	0.9399	0.9372
Sweden GBs	0.9635	0.9686	0.9687	0.9632	0.9667	0.9652
Switzerland GBs	0.9867	0.9856	0.9852	0.9857	0.9867	0.9865
UK GBs	0.9854	0.9774	0.9774	0.9800	0.9801	0.9816
US GBs	0.9728	0.9731	0.9725	0.9705	0.9712	0.9735

Note: U-statistics less than 1 show that measures of oil shocks are reliable predictor of the GBM.

Table 6
Single predictor: CW statistics (COVID-19).

	Supply						Demand					
		Out-Sample						*Out-Sample*				
	In-S	H = 1	H = 3	H = 6	H = 12	H = 24	In-S	H = 1	H = 3	H = 6	H = 12	H = 24
Denmark GBs	1.3889	1.4831	1.5485	1.5116	1.5928	1.4705	1.3312	1.1340	1.1665	1.0645	1.0150	0.7437
Euro GBs	1.2519	1.2290	1.2331	1.2115	1.2351	1.2332	0.7898	0.7899	0.7881	0.7898	0.7897	0.7894
Japan GBs	2.3489	2.3652	2.1005	2.3143	2.0551	2.3355	3.3203	2.9387	2.9503	3.0761	3.1072	3.0973
New Zealand GBs	1.6061	1.0804	0.8318	0.9574	0.8307	1.2680	4.815	3.6312	3.6568	3.8886	4.1122	4.5158
Norway GBs	2.6682	2.4878	2.2654	2.4064	2.2526	2.5249	4.7889	3.3623	3.4205	3.7476	3.8662	4.2511
Sweden GBs	1.9414	1.6301	1.1041	1.4261	1.1636	1.7088	4.2184	2.9339	2.9747	3.4020	3.4333	3.7625
Switzerland GBs	1.9493	0.98848	0.9749	0.9639	0.8598	1.4474	3.1964	2.2837	2.3632	2.4562	2.5573	2.7935
UK GBs	1.5684	0.8992	0.5789	0.7962	0.6068	1.0487	3.143	2.6876	2.709	2.6370	2.821	2.8581
US GBs	0.4172	0.4609	0.4210	0.4590	0.4164	0.4553	2.8006	2.0602	2.1072	2.3136	2.3482	2.4223

	Risk					
		Out-Sample				
	In-S	H = 1	H = 3	H = 6	H = 12	H = 24
Denmark GBs	0.8033	1.1080	1.0943	0.9643	0.8804	0.8148
Euro GBs	0.8838	0.8837	0.8834	0.8830	0.8834	0.8813
Japan GBs	2.9124	2.4561	2.4773	2.7313	2.8346	2.8173
New Zealand GBs	3.8859	2.8590	2.8311	3.0521	3.1998	3.3897
Norway GBs	4.6966	3.8906	3.8965	4.1241	4.2519	4.3920
Sweden GBs	3.7683	3.1854	3.1806	3.3562	3.4318	3.5321
Switzerland GBs	2.604	1.7649	1.8315	1.9352	2.0945	2.2977
UK GBs	2.604	1.7985	1.7915	1.8634	2.0197	2.2346
US GBs	3.159	3.1293	3.1592	3.2030	3.2556	3.2362

Note: CW measures the level of statistical significance. Values above 2.5 imply stat. Significance at the 5% level.

supply shocks fail to forecast both in- and out-of-sample returns across all investment horizons. These results are specific to the GBMs of Denmark, Europe, New Zealand, the UK, and the US. In other words, supply shocks will not help investors in these countries to maximise returns while investing in green bonds during the COVID-19 pandemic. We can also see how supply shocks only weakly forecast the in-sample, extreme-long-term (i.e. H = 24) returns for the Swedish bond market and fail to predict the short- and medium-term returns (i.e. H = 1 to H = 12). The case of Switzerland is similar but slightly different, such that supply shocks only forecast the in-sample returns and fail to predict the out-of-sample returns. However, supply shocks can be used to accurately forecast the in- and out-of-sample returns for Japanese and Norwegian green bond markets during distressed market conditions.

Similar to supply shocks, demand shocks also appear inefficient for accurately predicting green bond returns for both Denmark and Europe during the COVID-19 period. We also see how demand shocks can help forecast in-sample returns more accurately than the out-of-sample ones for GBMs in Switzerland and the US. However, the returns are accurately forecasted for the GBMs of Japan, New Zealand, Norway, Sweden, and the UK during the COVID-19 pandemic. In contrast, risk shocks cannot be used to forecast either the in-sample or out-of-sample green bond returns in Denmark and the US during the COVID-19 crisis period.

However, the results for the Japanese and Swiss markets are quite interesting, because risk shocks can be used to accurately forecast in-sample returns, but they only weakly predict the short-term (i.e. H = 1 and H = 6) returns for Japanese green bonds and the short- and medium-term (i.e. H = 1 to H = 12) returns for the Swiss GBM. In contrast, risk shocks can be used to correctly forecast the in- and out-of-sample returns of the green bond markets of New Zealand, Norway, Sweden, and the US. In other words, investors in these countries can use risk shocks as a tool for predicting green bond returns under distressed market conditions over both the short and long term.

5.1. Robustness checks

We conducted four of robustness checks. First, since the scope of the study captures different international markets, it is important to examine the time difference in the predictive model. As such, we used rolling average of two-day returns; the Theil-U statistics and CW test of this exercise are presented in Tables 7 and 8. We also checked whether the predictability analysis on volatility is the same as that of return analysis. These results are presented in Tables 9 and 10. Third, we accounted for some controls variables (inflation, interest rates, exchange rate, and industrial production index were used as controls). A section of the literature has shown that augmenting the predictive model with some macroeconomic fundamentals improves the performance of the forecasting model (Salisu et al., 2019; Ur Rehman et al., 2022). These results are presented in Tables 11 and 12. Finally, we examine the performance of the predictive model during the Russian-Ukrainian war, whose results are presented in Tables 13 and 14. Summarising the results of these checks, we show that our hitherto results are robust to the first two checks. We show that the performance of the model is weak for the Russia-Ukraine war era.

Tables 7–8 present results of the forecasting models using Theil-U statistics and CW test, respectively by employing rolling average of 2-days. We witness similar results like previously presented in Tables 3–4. Table 3 present coefficients of Theil-*U* test and the results suggest significant results for all markets across different horizons. Japanese green bonds market appears as the only exception, results of which remain insignificant for risk shocks. However, for both demand and supply driven shocks, the results of forecasting model appear significant. These results support our earlier findings that all oil related shocks i.e. demand, supply and risk driven shocks accurately predict the green bonds market. Table 8 present results of CW test using rolling average of 2-days. Interestingly, the forecasting ability of all the three shocks improved significantly using 2-days average returns. The coefficient for all the green bond markets are greater than the threshold of 2.5 suggesting significant results. Unlike our previous results presented in Table 4, supply shocks effectively predict returns of all green bonds market. Likewise, the forecasting ability of supply shocks has also increased significantly for the green bonds issued in Denmark, Europe and the UK. However, the forecasting ability of demand and risk shocks decreased significant for the green bonds market using rolling average of 2-days. The results still appear as significant however, strength of the forecasting ability for both supply and risk shocks decreases.

Predictability analysis on the basis of volatility of green bonds is presented in Tables 9–10. Table 9 present Theil's U statistics to forecast volatility in green bonds using three structural oil shocks. The results are similar to the forecasting ability of these disaggregate oil shocks for green bond returns as presented earlier. The forecasting ability of all the three oil shocks remain significant across all periods. Such results show that shift in the moment from returns to volatility does not affect the forecasting ability of oil shocks. Table 10 presents predictability analysis using CW statistics for green bonds volatility. We witness decreasing forecasting ability for supply shocks for the green bonds market of New Zealand and the UK. The predictability of Euro GBs also declines as we move from short- towards long-run period. However, for other remaining markets, supply shocks predict the volatility of green bonds. Likewise, demand- and risk-driven shocks successfully forecast volatility in green bonds market.

Tables 11–12 present estimates of the forecasting models using Theil's U and CW statistics in the presence of exchange rate, VIX and CPI as control variables. Results in Table 11 highlights good forecasting ability of supply, demand and risk shocks for green bonds of all the sampled countries. Therefore, introducing control variables along with disaggregated oil shocks predicts green bond yields. Afterwards, Table 12 predicts green bond yields using CW statistics for which results appear quite interesting. We see that the forecasting ability of supply-

Table 7
2-day average Theil U-statistics.

	Supply						Demand					
		Out-Sample						*Out-Sample*				
	In-S	H = 1	H = 3	H = 6	H = 12	H = 24	In-S	H = 1	H = 3	H = 6	H = 12	H = 24
Denmark GBs	0.9132	0.9090	0.9052	0.9094	0.9149	0.9138	0.9128	0.9140	0.8631	0.9819	0.9245	0.8654
Euro GBs	0.9131	0.9132	0.9055	0.9091	0.9146	0.9148	0.9124	0.9135	0.8642	0.8667	0.9229	0.9801
Japan GBs	0.8955	8955.1693	0.8933	0.9167	0.8340	0.8371	0.8874	0.9231	0.9104	0.9106	0.8974	0.9005
New Zealand GBs	0.9113	0.9114	0.9215	0.9260	0.9153	0.9153	0.9149	0.9149	0.8979	0.9009	0.8796	0.8826
Norway GBs	0.9101	0.9101	0.9204	0.9173	0.9140	0.9140	0.9147	0.9145	0.8997	0.9009	0.8657	0.9027
Sweden GBs	0.9005	0.9005	0.9341	0.9306	0.8941	0.8940	0.9097	0.9067	0.8853	0.8861	0.8758	0.9004
Switzerland GBs	0.8910	0.8913	0.9059	0.9547	0.9188	0.9191	0.9145	0.9250	0.9091	0.9096	0.9093	0.9230
UK GBs	0.8962	0.8963	0.8752	0.8813	0.8917	0.8922	0.8964	0.8973	0.9123	0.9116	0.9070	0.9070
US GBs	0.9037	0.9038	0.9145	0.9077	0.8914	0.8923	0.8884	0.8855	0.8866	0.8903	0.8742	0.9125

	Risk					
		Out-Sample				
	In-S	H = 1	H = 3	H = 6	H = 12	H = 24
Denmark GBs	0.9074	0.9032	0.8995	0.9036	0.9091	0.9080
Euro GBs	0.9073	0.9074	0.8997	0.9034	0.9088	0.9090
Japan GBs	0.8898	8898.1818	0.8876	0.9108	0.8287	0.8317
New Zealand GBs	0.9055	0.9056	0.9156	0.9201	0.9095	0.9095
Norway GBs	0.9043	0.9043	0.9145	0.9115	0.9082	0.9082
Sweden GBs	0.8948	0.8948	0.9282	0.9246	0.8884	0.8883
Switzerland GBs	0.8854	0.8856	0.9002	0.9486	0.9130	0.9133
UK GBs	0.8905	0.8906	0.8696	0.8757	0.8860	0.8865
US GBs	0.8979	0.8981	0.9086	0.9019	0.8857	0.8866

Note: U-statistics less than 1 demonstrate that measures of oil shocks are reliable predictors of GBM returns.

Table 8
2-day average: CW statistics.

	Supply						Demand					
		Out-Sample						*Out-Sample*				
	In-S	H = 1	H = 3	H = 6	H = 12	H = 24	In-S	H = 1	H = 3	H = 6	H = 12	H = 24
Denmark GBs	2.9943	2.9805	2.9682	2.9820	3.0000	2.9964	2.9931	2.9970	2.8302	3.2196	3.0315	2.8377
Euro GBs	2.9940	2.9943	2.9691	2.9811	2.9991	2.9997	2.9919	2.9955	2.8338	2.8419	3.0261	3.2136
Japan GBs	2.9364	29,364.0000	2.9292	3.0057	2.7348	2.7447	2.9097	3.0267	2.9853	2.9859	2.9427	2.9526
New Zealand GBs	2.9883	2.9886	3.0216	3.0363	3.0012	3.0012	3.0000	3.0000	2.9442	2.9541	2.8842	2.8941
Norway GBs	2.9841	2.9841	3.0180	3.0078	2.9970	2.9970	2.9994	2.9985	2.9501	2.9541	2.8386	2.9601
Sweden GBs	2.9529	2.9529	3.0630	3.0513	2.9316	2.9313	2.9829	2.9730	2.9028	2.9055	2.8719	2.9523
Switzerland GBs	2.9217	2.9226	2.9706	3.1305	3.0129	3.0138	2.9985	3.0330	2.9811	2.9826	2.9817	3.0264
UK GBs	2.9385	2.9391	2.8698	2.8899	2.9238	2.9256	2.9394	2.9424	2.9913	2.9892	2.9739	2.9739
US GBs	2.9631	2.9637	2.9985	2.9763	2.9229	2.9259	2.9130	2.9034	2.9070	2.9193	2.8665	2.9922
	Risk											
		Out-Sample										
	In-S	H = 1	H = 3	H = 6	H = 12	H = 24						
Denmark GBs	2.7947	2.7818	2.7703	2.7832	2.8000	2.7966						
Euro GBs	2.7944	2.7947	2.7712	2.7824	2.7992	2.7997						
Japan GBs	2.7406	27,406.4000	2.7339	2.8053	2.5525	2.5617						
New Zealand GBs	2.7891	2.7894	2.8202	2.8339	2.8011	2.8011						
Norway GBs	2.7852	2.7852	2.8168	2.8073	2.7972	2.7972						
Sweden GBs	2.7560	2.7560	2.8588	2.8479	2.7362	2.7359						
Switzerland GBs	2.7269	2.7278	2.7726	2.9218	2.8120	2.8129						
UK GBs	2.7426	2.7432	2.6785	2.6972	2.7289	2.7306						
US GBs	2.7656	2.7661	2.7986	2.7779	2.7280	2.7308						

Notes: CW measures the level of statistical significance. Values above 2.5 imply stat. Significance at 5%.

Table 9
Volatility: Theil's U-statistics.

	Supply						Demand					
		Out- Sample						*Out- Sample*				
	In-S	H = 1	H = 3	H = 6	H = 12	H = 24	In-S	H = 1	H = 3	H = 6	H = 12	H = 24
Denmark GBs	0.7358	0.7359	0.7387	0.7367	0.7374	0.7378	0.7347	0.7347	0.7353	0.7357	0.7360	0.7366
Euro GBs	0.7357	0.7357	0.7360	0.7367	0.7373	0.7377	0.7348	0.7348	0.7354	0.7358	0.7361	0.7367
Japan GBs	0.7027	0.7029	0.7030	0.7041	0.7044	0.7057	0.6440	0.6439	0.6439	0.6445	0.6454	0.6461
New Zealand GBs	0.7398	0.7397	0.7397	0.7399	0.7400	0.7399	0.7290	0.7291	0.7293	0.7292	0.7292	0.7296
Norway GBs	0.7219	0.7219	0.7215	0.7224	0.7214	0.7216	0.7224	0.7216	0.7220	0.7210	0.7217	0.7219
Sweden GBs	0.7315	0.7301	0.7300	0.7309	0.7305	0.7319	0.7125	0.7127	0.7124	0.7152	0.7156	0.7167
Switzerland GBs	0.7297	0.7297	0.7299	0.7305	0.7313	0.7317	0.7186	0.7186	0.7190	0.7194	0.7198	0.7203
UK GBs	0.7333	0.7333	0.7336	0.7333	0.7339	0.7344	0.7299	0.7299	0.7300	0.7298	0.7302	0.7307
US GBs	0.6981	0.6984	0.6983	0.6987	0.6987	0.6998	0.6306	0.6306	0.6301	0.6308	0.6310	0.6322
	Risk											
		Out- Sample										
	In-S	H = 1	H = 3	H = 6	H = 12	H = 24						
Denmark GBs	0.7335	0.7335	0.7339	0.7339	0.7339	0.7341						
Euro GBs	0.7336	0.7336	0.7340	0.7340	0.7339	0.7341						
Japan GBs	0.6945	0.6945	0.6944	0.6947	0.6956	0.6969						
New Zealand GBs	0.7339	0.7339	0.7339	0.7336	0.7336	0.7341						
Norway GBs	0.7343	0.7342	0.7339	0.7344	0.7347	0.7348						
Sweden GBs	0.7337	0.7338	0.7336	0.7344	0.7350	0.7353						
Switzerland GBs	0.7254	0.7254	0.7258	0.7260	0.7258	0.7261						
UK GBs	0.7381	0.7381	0.7381	0.7381	0.7383	0.7381						
US GBs	0.7139	0.7138	0.7135	0.7138	0.7143	0.7156						

Note: U-statistics less than 1 demonstrate that measures of oil shocks are reliable predictors of GBM returns.

and demand-driven shocks deteriorates significantly using control variables for almost all countries. The only exception is the green bonds market in Euro for which the forecasting models works well in case of demand- as well as supply-driven shocks. On the contrary, we see good predictability analysis for risk shocks where all the coefficients remain significant.

Tables 13-14 present the forecasting ability of disintegrated oil shocks during the Russian-Ukrainian war period. Results in Table 11 appear quite different from the full sample results as we witness much evidence of insignificant results during this turbulent period. Supply shocks highlight no predictive ability for the green bonds market in New Zealand, Norway and Sweden in the long-run period. Besides these markets, the predictive ability of supply shocks remains significant for the green bonds market of other countries. On the other hand, demand driven shocks highlight better predictive analysis for the green bonds markets except Switzerland (throughout the period) and New Zealand (in the long-run). Table 12 presents CW statistics which highlight poor ability of disaggregated shocks to forecast green bonds market. Neither type of oil shock highlights any signs of forecasting ability for any green bonds market. Such results are indicative of the fact that the forecasting ability of oil shocks during the Russian-Ukrainian war period appears insignificant.

Table 10
Volatility: CW statistics.

	Supply						Demand					
		Out-Sample						Out-Sample				
	In-S	H = 1	H = 3	H = 6	H = 12	H = 24	In-S	H = 1	H = 3	H = 6	H = 12	H = 24
Denmark GBs	2.6374	2.2744	2.5841	2.4342	2.6374	2.2156	5.9907	5.9907	5.9729	5.8497	5.9474	5.8264
Euro GBs	2.6507	2.6507	2.5996	2.4498	2.2899	2.2289	5.9274	5.9285	5.7742	5.8009	5.9041	5.9263
Japan GBs	7.8821	7.8721	7.8943	7.8854	7.9199	7.8699	11.3975	11.4041	11.4363	11.4596	11.4263	11.4152
New Zealand GBs	1.2599	1.1933	1.3009	1.2909	1.2665	1.2143	6.0107	6.0473	6.1039	6.2682	6.3292	6.1106
Norway GBs	5.4834	5.4779	5.6055	5.6166	5.8752	6.0451	5.1693	5.1793	5.3669	5.2448	5.2037	5.2181
Sweden GBs	7.1473	7.1817	7.2261	6.9353	7.1606	6.7366	5.5001	5.4612	5.5400	5.2448	5.1215	5.0461
Switzerland GBs	5.2581	5.0216	5.2181	5.1526	5.2625	4.9617	8.5492	8.5459	8.4771	8.4427	8.5648	8.5503
UK GBs	2.4509	2.4487	2.4231	2.4864	2.4331	2.3821	3.5687	3.5742	3.6053	3.6808	3.5453	3.3822
US GBs	6.3792	6.5512	6.4114	6.4802	6.3781	6.5457	9.8013	9.8024	9.8857	9.8912	9.9023	9.7702

	Risk					
		Out-Sample				
	In-S	H = 1	H = 3	H = 6	H = 12	H = 24
Denmark GBs	3.7718	3.7718	3.5975	3.4987	3.4355	3.2701
Euro GBs	3.7396	3.7396	3.5631	3.4710	3.4044	3.2401
Japan GBs	12.7783	12.7850	12.8327	12.8571	12.8605	12.8882
New Zealand GBs	5.9463	5.9296	5.9696	6.0373	6.1128	6.0961
Norway GBs	6.8709	6.8731	7.0407	6.8831	7.0851	7.2605
Sweden GBs	4.0776	4.0776	3.8892	3.7824	3.7140	3.5352
Switzerland GBs	7.7556	7.7511	7.6923	7.6646	7.6479	7.6024
UK GBs	5.3691	5.3713	5.3624	5.4501	5.3868	5.2914
US GBs	3.6563	3.6566	3.6797	3.6934	3.7153	3.7216

Notes: CW measures the level of statistical significance. Values above 2.5 imply stat. Significance at 5%.

Table 11
Control variables: Theil's U statistics (COVID-19).

	Supply						Demand					
		Out-Sample						Out-Sample				
	In-S	H = 1	H = 3	H = 6	H = 12	H = 24	In-S	H = 1	H = 3	H = 6	H = 12	H = 24
Denmark GBs	0.8242	0.8161	0.8172	0.8188	0.8200	0.8209	0.8295	0.8231	0.8234	0.8258	0.8273	0.8285
Euro GBs	0.9011	0.9028	0.9012	0.9014	0.9011	0.9010	0.9061	0.9016	0.9020	0.9021	0.9009	0.9020
Japan GBs	0.8125	0.8110	0.8103	0.8059	0.8059	0.8084	0.7710	0.7663	0.7707	0.7569	0.7592	0.7653
New Zealand GBs	0.7945	0.7984	0.7986	0.7977	0.7970	0.7958	0.7600	0.7614	0.7633	0.7613	0.7636	0.7620
Norway GBs	0.8451	0.8405	0.8414	0.8418	0.8412	0.8425	0.7480	0.7220	0.7261	0.7298	0.7403	0.7424
Sweden GBs	0.8273	0.8303	0.8309	0.8286	0.8277	0.8276	0.7856	0.7719	0.7741	0.7730	0.7794	0.7814
Switzerland GBs	0.8294	0.8331	0.8326	0.8328	0.8328	0.8309	0.8111	0.8138	0.8130	0.8136	0.8142	0.8124
UK GBs	0.8311	0.8339	0.8334	0.8332	0.8328	0.8323	0.8138	0.8158	0.8153	0.8162	0.8153	0.8164
US GBs	0.8323	0.8318	0.8318	0.8317	0.8318	0.8318	0.7663	0.7289	0.7292	0.7348	0.7438	0.7507

	Risk					
		Out-Sample				
	In-S	H = 1	H = 3	H = 6	H = 12	H = 24
Denmark GBs	0.7976	0.7898	0.7908	0.7924	0.7935	0.7944
Euro GBs	0.8329	0.8416	0.8401	0.8403	0.8400	0.8399
Japan GBs	0.8484	0.8469	0.8462	0.8416	0.8416	0.8442
New Zealand GBs	0.8788	0.8832	0.8834	0.8824	0.8816	0.8803
Norway GBs	0.8376	0.8331	0.8340	0.8343	0.8337	0.8350
Sweden GBs	0.8786	0.8817	0.8824	0.8799	0.8789	0.8788
Switzerland GBs	0.8808	0.8847	0.8842	0.8843	0.8844	0.8824
UK GBs	0.8826	0.8856	0.8850	0.8848	0.8844	0.8839
US GBs	0.8839	0.8833	0.8833	0.8832	0.8834	0.8834

Note: U-statistics less than 1 show that measures of oil shocks are reliable predictor of the GBM.

6. Conclusion

The development of GBMs has garnered significant attention from investors, policymakers, and scholars in recent years, mainly due to the growing global awareness and concern about climate change. Among the vast selection of existing literature, when examining the role of green investment in portfolio strategies, Zerbib (2019) and Bachelet et al. (2019) have posited that investors pay a premium for green bonds. Such a finding is supported by the increasing level of investment in green bonds by investors in both developed and developing countries (Banga, 2019; Tu et al., 2020). However, whether green bonds outperform other asset classes is a question that has yet to be answered, but some underlying factors can certainly play an important role in determining returns for green investments, with these mainly including varying economic conditions and the performance of traditional bond and equity markets in comparison to their energy counterparts. Given the importance of oil to the world economy, its significance cannot be ignored for any kind of investment, both conventional and more recently financialised asset classes. Consequently, to build upon the existing literature, we examined the role of different oil shocks, (i.e. demand, supply, and risk), following the example of Ready (2018), in predicting green bond returns for a wide array of GBMs including those in Denmark, Europe,

Table 12
Control variable: CW statistics (COVID-19).

	Supply						Demand					
		Out-Sample						*Out-Sample*				
	In-S	H = 1	H = 3	H = 6	H = 12	H = 24	In-S	H = 1	H = 3	H = 6	H = 12	H = 24
Denmark GBs	2.4726	2.4483	2.4516	2.4564	2.46	2.4627	2.4885	2.4693	2.4702	2.4774	2.4819	2.4855
Euro GBs	2.7033	2.7084	2.7036	2.7042	2.7033	2.703	2.7183	2.7048	2.706	2.7063	2.7027	2.706
Japan GBs	2.4375	2.433	2.4309	2.4177	2.4177	2.4252	2.313	2.2989	2.3121	2.2707	2.2776	2.2959
New Zealand GBs	2.3835	2.3952	2.3958	2.3931	2.391	2.3874	2.28	2.2842	2.2899	2.2839	2.2908	2.286
Norway GBs	2.5353	2.5215	2.5242	2.5254	2.5236	2.5275	2.244	2.166	2.1783	2.1894	2.2209	2.2272
Sweden GBs	2.4819	2.4909	2.4927	2.4858	2.4831	2.4828	2.3568	2.3157	2.3223	2.319	2.3382	2.3442
Switzerland GBs	2.4882	2.4993	2.4978	2.4984	2.4984	2.4927	2.4333	2.4414	2.439	2.4408	2.4426	2.4372
UK GBs	2.4933	2.5017	2.5002	2.4996	2.4984	2.4969	2.4414	2.4474	2.4459	2.4486	2.4459	2.4492
US GBs	2.4969	2.4954	2.4954	2.4951	2.4954	2.4954	2.2989	2.1867	2.1876	2.2044	2.2314	2.2521

	Risk					
		Out-Sample				
	In-S	H = 1	H = 3	H = 6	H = 12	H = 24
Denmark GBs	2.6374	2.6115	2.6150	2.6202	2.6240	2.6269
Euro GBs	2.8835	2.8890	2.8838	2.8845	2.8835	2.8832
Japan GBs	2.6000	2.5952	2.5930	2.5789	2.5789	2.5869
New Zealand GBs	2.5424	2.5549	2.5555	2.5526	2.5504	2.5466
Norway GBs	2.7043	2.6896	2.6925	2.6938	2.6918	2.6960
Sweden GBs	2.6474	2.6570	2.6589	2.6515	2.6486	2.6483
Switzerland GBs	2.6541	2.6659	2.6643	2.6650	2.6650	2.6589
UK GBs	2.6595	2.6685	2.6669	2.6662	2.6650	2.6634
US GBs	2.6634	2.6618	2.6618	2.6614	2.6618	2.6618

Note: CW measures the level of statistical significance. Values above 2.5 imply stat. Significance at the 5% level.

Table 13
Russia-Ukraine war: Theil U statistics.

	Supply				Demand				Risk			
		Out-of-Sample				Out-of-Sample				Out-of-Sample		
	In-S	H = 10	H = 20	H = 30	In-S	H = 10	H = 20	H = 30	In-S	H = 10	H = 20	H = 30
Denmark GBs	0.9981	0.9935	0.9894	0.9940	1.000	0.9988	0.9977	0.999	0.9434	1.0732	1.0105	0.9459
Euro GBs	0.9980	0.9981	0.9897	0.9937	0.9997	0.9999	0.9973	0.9985	0.9446	0.9473	1.0087	1.0712
Japan GBs	0.9788	09788	0.9764	1.0019	0.9116	0.9149	0.9699	1.0089	0.9951	0.9953	0.9809	0.9842
New Zealand GBs	0.9961	0.9962	1.0072	1.0121	1.0004	1.0004	1.0000	1.0000	0.9814	0.9847	0.9614	0.9647
Norway GBs	0.9947	0.9947	1.0060	1.0026	0.9990	0.9990	0.9998	0.9995	0.98336	0.9847	0.9462	0.9867
Sweden GBs	0.9843	0.9843	1.0210	1.0171	0.9772	0.9771	0.9943	0.9910	0.9676	0.9685	0.9573	0.9841
Switzerland GBs	0.9739	0.9742	0.9902	1.0435	1.0043	1.0046	0.9995	1.0110	0.9937	0.9942	0.9939	1.0088
UK GBs	0.9795	0.9797	0.9566	0.9633	0.9746	0.9752	0.9798	0.9808	0.9971	0.9964	0.9913	0.9913
US GBs	0.9877	0.9879	0.9995	0.9921	0.9743	0.9753	0.9710	0.9678	0.9690	0.9731	0.9555	0.9974

Table 14
Russia-Ukraine: CW statistics.

	Supply				Demand				Risk			
		Out-of-Sample				Out-of-Sample				Out-of-Sample		
	In-S	H = 10	H = 20	H = 30	In-S	H = 10	H = 20	H = 30	In-S	H = 10	H = 20	H = 30
Denmark GBs	0.3781	0.3769	1.2855	0.9446	1.6006	0.2084	1.0651	1.5727	0.1981	0.1800	0.5639	0.4035
Euro GBs	0.3846	0.3829	1.2611	0.9216	1.6132	1.5821	1.0944	0.2205	0.2706	0.2516	0.6108	0.4512
Japan GBs	1.3103	1.3099	1.4984	0.5711	0.7629	0.7605	1.4755	1.7060	2.7585	2.7470	2.1564	0.9827
New Zealand GBs	0.5369	0.5368	0.3870	0.6398	1.4819	1.3579	2.2596	2.2918	0.1025	0.0988	0.0498	0.0204
Norway GBs	0.7899	0.7931	0.6292	0.1726	1.2263	1.2005	1.8247	1.2616	0.6941	0.7070	0.1774	0.5250
Sweden GBs	1.0279	1.0282	0.0597	0.2432	1.7158	1.6976	1.8396	1.6592	1.3254	1.3276	1.0117	1.205
Switzerland GBs	1.4190	1.4142	1.3743	0.3733	0.7880	0.7489	0.9481	0.3948	0.3729	0.3619	0.6074	0.0647
UK GBs	1.332	1.3343	2.0383	2.0300	0.4403	0.5075	0.9333	1.1620	1.6779	1.6685	1.6870	1.6937
US GBs	1.0883	1.0869	0.7752	1.0868	1.3889	1.3071	1.8248	1.1422	1.3663	1.3530	1.6338	1.8969

Switzerland, New Zealand, Sweden, Japan, Norway, the UK, and the US for a period spanning from December 2, 2008 to July 11, 2021. As a diagnostic test, we employed the adjusted OLS estimator that was introduced by Westerlund and Narayan (2012, 2015) to avoid serious problems related to persistence, endogeneity, and heteroscedasticity.

We found some interesting results, which are summarized as follows: First, we found support for predictability irrespective of the particular oil-related shock for all green bond indices except the UK GBM. More specifically, demand shocks only fail to predict green bond returns in the case of the UK, yet they can be used to accurately forecast all the other considered green bond markets. Second, Theil's U statistic is relatively more significant for forecasting green bond returns across all investment horizons (i.e. H = 1 to H = 24) when considering supply, demand, and risk shocks. Third, green bond returns in Japan and the US are more accurately predicted by all three shocks. Fourth, the CW statistics highlight that supply shock is the only predictor that fails to forecast the in- and out-of-sample returns for the New Zealand GBM. However, the results for the COVID-19 crisis period appear to be heterogeneous. The measure based on Theil's U shows that only oil supply shocks fail to help forecast both the in- and out-of-sample returns for UK green bonds during the COVID-19 pandemic. Furthermore, the CW statistics indicate that all three oil shocks fail to predict both in- and out-of-sample returns for the specific green bond indices of Denmark and Europe during COVID-19, suggesting that these oil shocks are not helpful for forecasting future green bond returns during distressed market conditions.

Our findings carry several implications for practitioners and investors. Green bond returns seem to be significantly predictable when considering oil market shocks, and this should surely be useful for investors in helping them to rebalance their portfolios and gain maximal returns from their investments in the GBM. In addition, this predictability is relatively strong across multiple investment horizons in the cases of the Japanese and American GBMs, so this revelation may be appealing to both short-term (i.e. less than six months) and long-term (i.e. up to 24 months) investors in these markets. To put it bluntly, monitoring the variation in the oil market can help investors to beat the markets and gain additional returns from trading in GBMs. Finally, our findings about the variation in predictability during the COVID-19 crisis period also have implications for investors looking to reshape their investment strategies. In this way, investors can overweight or underweight their investments in GBMs according to forecasts based on oil market shocks. Any change in market conditions could then prompt investors to shift their investments and rebalance their portfolios. We also provide future direction to our work by sampling international green bonds to consider the effect of heterogeneity across different markets.

CRediT authorship contribution statement

Mobeen Ur Rehman: Conceptualization, Data curation, Software, Validation. **Ibrahim D. Raheem:** Methodology, Software, Formal analysis. **Rami Zeitun:** Investigation, Writing – review & editing. **Xuan Vinh Vo:** Project administration, Supervision, Resources. **Nasir Ahmad:** Writing – original draft.

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Appendix A. Supplementary data

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