Oil shocks and volatility of green investments: GARCH-MIDAS analyses

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Abstract

This study examines how market volatility of five green investments (Standard & Poor's - S&P [Green bond select index and Green bond index] and Morgan Stanley Capital International - MSCI [Global alternative energy index, Global pollution prevention index, and Global green building index]) respond to oil shocks; using the Generalized Autoregressive Conditional Heteroscedasticity with Mixed Data Sampling (GARCH-MIDAS) modelling framework. We employ Baumeister and Hamilton's decomposed oil shocks: economic activity shocks, oil consumption demand shocks, oil inventory demand shocks, and oil supply shocks; each in their original levels, as well as their negatively and positively disaggregated levels. Our findings show homogeneous and heterogeneous responses of green investments volatility to variants of oil shocks. Asymmetry effect is also evidenced, given the differences between the estimated effect of positive and negative oil shocks on the volatility of green investments.

Keywords: GARCH-MIDAS; green bond; oil shocks; asymmetry
JEL Classifications: C32; G12; G15

1. Introduction

Changes in oil prices, using level value or log-differences as proxy variables, have been applied in many empirical literature; but an attempt to break oil price fluctuations into four sources has only recently been documented in the literature (Baumeister and Hamilton, 2019), as a follow-up to the initial attempt to disaggregate oil shocks into their various components to determine their distinct impacts (Kilian, 2009; Kilian and Park, 2009). These oil shocks, which include economic activity, supply, aggregate demand, and precautionary demand shocks, are defined based on perceived causes of oil price fluctuations, and are now being increasingly used in the literature (see Adekoya and Oliyide, 2020; Salisu and Gupta, 2020; Adekoya, Ogunbowale, Akinseye and Oduyemi, 2021). Supply shock expectations of oil are majorly influenced by the availability of crude oil supply and the uncertainty regarding its continuous availability of its production. For the demand shock, expectations are influenced by fluctuations in the global business cycle as well as the uncertainty regarding its unanticipated shortfalls in the levels of available supply relative to the anticipated levels of oil demand (Hamilton, 2009; Kilian, 2008). These market imbalances enrich oil pricing episodes in the form of oil price shocks that are expected to reflect disruptions in the oil market. Oil pricing has gone through structural changes in the international market, in which the first phase was the integrated and regulated market that ended in 1972. The second phase was the transitional period in the aftermath of the first and second oil shocks, and this spanned 1973 to 1984; while the third phase was the commodity and deregulated market which started in 1986 and it is still ongoing. During this last phase, oil prices are being determined conditionally to expectations about supply-demand tightness (Mitchell, 2002).

Without energy sources, sustainability cannot be achieved. Thus, investors are shifting towards green investment in order to support environment-friendly goods and services. Green investments are recently introduced traded environmental indexes which consist of companies that use eco-friendly production processes and develop green infrastructure (Dutta, Jana and Das, 2020). These indexes include prominent two green bonds and three green stocks. The green stocks are the Morgan Stanley Capital International (MSCI) global alternative energy index, the MSCI global pollution prevention index, and the MSCI global green building index, while the green bonds are the Standards and Poors (S&P) Green bond select index, and S&P

Green bond index. Green investments, like other assets, are prone to oil shocks and their volatility due to unforeseen circumstances in the oil markets mentioned earlier. It is noted in Park et al. (2020) that green assets are sensitive to oil shocks and induced volatility by these shocks is very persistent in the green investment market, leaving the market in a state of inefficiency (Adekoya et al., 2021). Thus, investors are likely to be disinterested, raising severe fears which can hinder them from achieving common goal of environmental sustainability.

Quite a few literature have investigated the causal relationships between oil shocks and green investments. Kang, Ratti, and Yoon (2014) found that oil-related demand and supply shocks jointly contributed about 30% variation in the US bond returns in the long run, while oil demand shocks influenced Treasury bill returns significantly. Kanamura (2020) found a positive correlation between green bonds and oil prices. The author also found positive correlations between the returns of green bond returns and crude oil. Dutta, Jana, and Das (2020) considered WTI oil returns in investigating the reactions of oil price shocks to green investments using Markov switching regime regression. The authors first found the insignificant effect of crude oil prices on green investments, while further analysis indicated switching between low and high volatility regimes for green investment. Lee, Lee, and Li (2020) investigated Granger-causality by using quantile analysis to obtain bi-directional causality from disaggregated oil shocks to the green bond index for the lower quantiles. Azhgaliyeva, Mishra, and Kapsalyamova (2021) applied multilevel longitudinal random intercept and random coefficient models in investigating the impact of disentangled oil price shocks on green bond issuance. Results showed that, of all the four disaggregated oil shocks, oil supply shocks only affected the green bond issuance positively.

From the foregoing, our research contributes to the extant literature by assessing the nexus between variants of oil demand and supply shocks on green investments volatility, using a mixed data sampling (MIDAS) framework in a conventional volatility (GARCH) model. The MIDAS regression allows for the estimation of the nexus between two or more variables of different time frequencies, say monthly with quarterly variables (Ghysels, 2017; Ghysels et al., 2019). The extension of the framework to volatility modelling is known as GARCH-MIDAS, which uses low (monthly) frequency macroeconomic series to predict high (daily) frequency asset prices[1]. Though, the green investments' prices exist at a daily frequency, aggregating them to a lower frequency, say monthly will lead to loss of vital information (Clements and Calvao, 2008; Das, Demirer, Gupta and Mangisa, 2019).

The study is motivated by the newfound relevance of historically decomposed oil price fluctuations, into oil shocks, for predicting conditional volatility in high-frequency datasets (as in our study on green investments). While the oil markets' price dynamics may have a triggering effect on the entire energy markets, the "greenness" clamoured for in green investment requires energy. In another explanation, the low oil price will increase oil demands, leading to reduced incentives and interests by social responsibility investors. In contrast, an increase in oil price leads to an increase in incentives, resulting in increases in the equity price of green investments (Bondia et al., 2016; Broadstock and Cheng, 2019; Dutta et al., 2020; Lee, Lee, and Li, 2020). Also, the GARCH-MIDAS regression methodological approach is still in the infancy stage of its applications, and this will yield the findings that would be of interest to green investors. Summarily, with the GARCH-MIDAS model framework, we are able to obtain more robust results than with the univariate model; since the former adequately incorporates Baumeister and Hamilton's (2019) decomposed oil shocks (monthly) as a predictor for daily frequency green bonds and stocks' volatility, without information loss due to data aggregation to achieve equal time-frequency. To the best of our knowledge, this is the

[1] Salisu and Ogbonna (2019) examined a MIDAS variant (ADL-MIDAS) that uses a high frequency predictor variable for the prediction of a low frequency dependent variable.

first paper to analyze the predictions of green investments' volatility using Baumeister and Hamilton's (2019) decomposed oil shocks, and the GARCH-MIDAS as an analysis framework.

Following from the introductory section, subsequent sections are structured as follows: Section 2 details the GARCH-MIDAS methodology; Section 3 summarizes and highlights inherent data issues with preliminary tests; Section 4 discusses the empirical findings, and Section 5 renders the conclusion.

2. Methodology

One thrilling contribution of this study is the adaptation of the MIDAS framework, which allows for the combination and analysis of non-uniform-frequency variables within one analytical framework. This ensures that the possibility of a loss of information is circumvented in the oil shocks-green asset market nexus. The four oil shock variables act as proxies for oil price dynamics, which are decomposed into sources of oil shocks in the market. Thus, these oil shock variables allow for a more adequate and specific assessment of the relative contribution of each oil shocks sources to green investments' returns that determine the level of corresponding stocks market fears.

In the MIDAS framework, the predicted series are the daily green investment returns while the predictor series is the monthly oil shocks. The GARCH – MIDAS model then uses the information in the high frequency (metaseries) by making the low-frequency variable to enter directly into the specification of the long-term component.

The daily green asset returns $r_{i,t}$ are obtained as $r_{i,t} = 100 \times ln\left[G_{i,t}/G_{i-1,t}\right]$ where $G_{i,t}$ denotes the green investments' index value on day i of month t; $t = 1, \dots, T$ denotes the frequency in months; while $i = 1, \dots, N_t$ denotes the frequency in days, with N_t representing the number of days in a month t. The GARCH – MIDAS model is specified in two parts: the unconditional mean part and the conditional variance part; and is defined in equation (1) as

$$r_{i,t} = \mu + \sqrt{\tau_t \times h_{i,t}} \times Z_{i,t}\,,\; Z_{i,t} \mid \mathrm{I}_{i-1,t} \sim N(0,1) \tag{1}$$

where μ is a constant that represents the unconditional mean of green investments returns; and $\mathrm{I}_{i-1,t}$ defines the available historical information as at day $i-1$ of month t; $h_{i,t}$ and (τ_i) are respectively the short-run fluctuations and the long-term volatility in a rolling window framework, and are both constituents of the conditional variance component in equation (1). The short-run term, $h_{i,t}$ is at a higher (daily) frequency series that follows a stationary GARCH (1,1) process,

$$h_{i,t} = (1-\alpha-\beta) + \frac{\alpha\left(r_{i,t},t-\mu\right)^2}{\tau_i} + \beta\bar{h}_{i-1,t} \tag{2}$$

where α and β are respectively the ARCH and GARCH parameters, which are conditioned as $\alpha > 0,\ \beta \geq 0$ and $\alpha + \beta < 1$ for the stationary covariance process. The value of $\alpha + \beta$ indicates the degree of persistence. The long-term monthly frequency-varying term is transformed to a daily frequency as the days across months t are rolled back without keeping track of it; and is defined in equation (3) as

$$\tau_i^{(rw)} = m_i^{(rw)} + \theta_i^{(rw)} \sum_{k=1}^{K\prime} \phi_k(w_1, w_2) X_{i-k}^{rw} \tag{3}$$

where the superscripted (rw) implies the application of a rolling window; m is the long-run constant term; θ is the slope coefficient which could be the summed weighted realized volatilities when no explanatory variable is included or the measure of the predictability of the included exogenous/explanatory variable (monthly oil shocks) for daily green asset returns; X_{i-k}^{rw} is our explanatory variable of interest (i.e. green investments); and $\phi_k(w_1, w_2)$ is the two-parameter beta polynomial function. This is given as,

$$\phi_k(w_1, w_2) = \frac{\left[{}^{k}/_{k+1}\right]^{w_1-1} \times \left[1-{}^{k}/_{(k+1)}\right]^{w_2-1}}{\sum_{j=1}^{k}\left[{}^{j}/_{k+1}\right]^{w_1-1} \times [1-j(k+1)]^{w_2-1}} \tag{4}$$

where $\phi_k(w_1, w_2) \geq 0, k = 1, \ldots, K$ for parameters identifiability. However, it is more convenient to employ a one-parameter beta polynomial weighting function due to its flexibility (Colacito et al., 2011). Our study, therefore, draws from this feat that allows for an easy transformation of a two-parameter beta polynomial function in equation (4) to a one-parameter beta polynomial function in equation (5), by equating w_1 to unity and $w_2 = w$; wherein a monotonically decreasing weighting function can be optimally obtained (Engle et al. 2013). Hence, the one-parameter beta function is given in equation (5)

$$\phi_k(w_1, w_2) \Leftrightarrow \phi_k(w) = \frac{\left[1 - k/(K+1)\right]^{w-1}}{\sum_{j=1}^{K}\left[1 - j/(K+1)\right]^{w-1}} \tag{5}$$

where weights are greater than zero and sum to unity. Given the possibility of difference in the impact of different lag observations and taking cognisance far back information should not be accorded an equal level of importance as immediate past observation, more recent observation lags are weighted higher than distant observation lags by imposing the restriction, $w > 1$.

3. Data presentation and preliminary analysis

We consider herein four global oil shock measures. These include economic activity shocks (EAS), oil consumption demand shocks (OCDS), oil inventory demand shocks (OIDS) and oil supply shocks (OSS). An updated version of the disaggregated oil shocks data; which were previously analyzed by Baumeister and Hamilton (2019) and Salisu and Gupta (2020) were retrieved from https://sites.google.com/site/cjsbaumeister/research (website of Professor Christiane Baumeister). The source to obtain the data used by Professor Christiane Baumeister is the U.S. Energy Information Administration (EIA) and the datasets are publicly available on the website. The calculations are also indicated clearly in the excel file of the dataset and the data are often updated by the researcher, and it should not be a concern for authors to generate their own oil shocks to analyse the impact of oil on their variable of interest. While another author such as Ready (2018) has suggested an oil shock routine in which oil is majorly disaggregated into demand and supply shocks components, in daily frequency but these datasets are not readily available like that of Professor Christiane Baumeister which has gained wider empirical applications.[2] The retrieved monthly frequency datasets span from September 2010 to June 2021, to cover more recent periods. Daily data of green bonds and green stocks, including S&P Green bond select index (SPGRSLL), S&P Green bond index (PGRBND), MSCI global alternative energy index (MSGLAEL, MSCI global pollution prevention index (MSGLPPL), and MSCI global green building index (MSGLGBL); were retrieved from Datastream. The daily dataset spans from 1 September 2010 to 31 June 2021. We present the dynamics of each pair of green investments indices and oil shocks in Figure 1, with evidence of volatility in the paired (green returns and oil shocks) series that suggests the appropriateness of a volatility modelling framework. Again, the GARCH-MIDAS model qualifies for this purpose.

[2] Ready (2018) daily disaggregated oil shocks are not readily available as at the time of the analysis, therefore one would have applied it in an alternative model different from MIDAS regression.

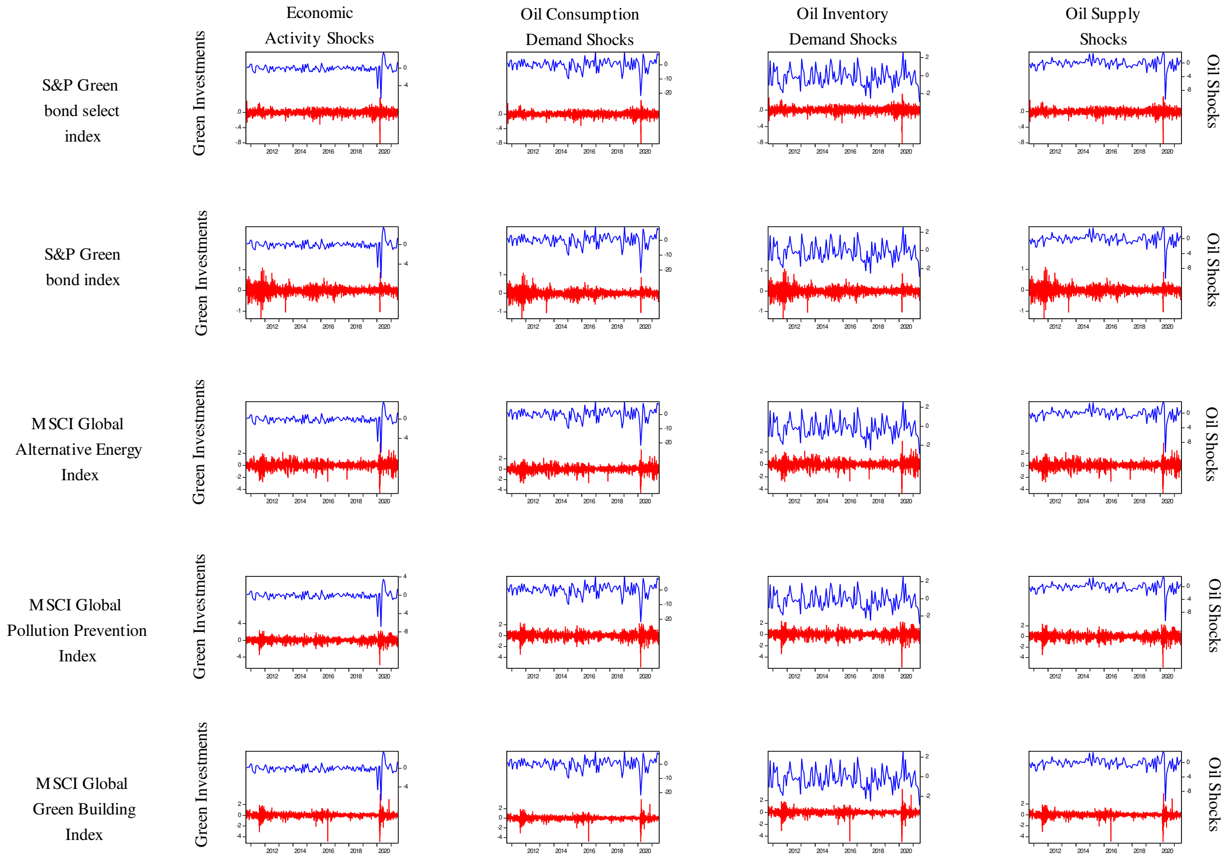

Figure 1: Graphical Display of the Relationship between Daily Green Investments returns and Monthly Oil Shocks

Table 1 presents the summary statistics of the daily returns of green investments, and monthly oil shock proxies, which amount to 2826 and 130 data points, respectively. On average, the returns on green investments ranged between -0.0002 (SPGRBND) and 0.0222 (MSGLPPL), with the measure of the spread of the green investment data around their mean being least (highest) in SPGRSLL (MSGLAEL). All the green investment returns were negatively skewed (asymmetric) and leptokurtic (exhibiting kurtosis values exceeding the normal threshold of 3); as consistent with any returns series (Salisu and Oloko, 2015; Salisu, Ogbonna and Adediran, 2021; among others) and an indication of the non-normality of the data distribution. SPGRBND and MSGLPPL were the most and least volatile series among the green investments series, given that the corresponding absolute coefficient of variation is the highest and smallest, respectively.

Table 1: Descriptive Statistics

Ticker	Mean	Std. Dev.	Skewness	Kurtosis	CV	N	Frequency
Returns of Green Investments							
SPGRSLL	0.0017	0.0680	-1.0138	14.1720	3955.1163	2826	Daily
SPGRBND	-0.0002	0.1696	-0.3586	9.2010	-74071.1790	2826	Daily
MSGLAEL	0.0041	0.5658	-0.6044	8.8646	13830.6038	2826	Daily
MSGLPPL	0.0222	0.5522	-0.7582	10.2156	2484.0351	2826	Daily
MSGLGBL	0.0128	0.4467	-1.4672	24.6061	3490.2407	2826	Daily
Oil Shocks							
EAS	-0.0691	1.0109	-2.4318	21.6352	-1462.7402	130	Monthly
OCDP	0.0204	4.1798	-1.3047	7.9303	20513.1527	130	Monthly
OIDS	-0.1776	1.0056	0.2083	2.9016	-566.3329	130	Monthly
OSS	-0.1640	1.4898	-2.6972	21.0411	-908.5663	130	Monthly

Note: Std. Dev. and CV are the standard deviation and coefficient of variation, respectively while N is the sample size of each variable. *SPGRSLL* is the S&P Green bond select index; *SPGRBND* is the S&P Green bond index; *MSGLAEL* is the MSCI global alternative energy index; *MSGLPPL* is the MSCI global pollution prevention index; *MSGLGBL* is the MSCI global green building index; *EAS* is the economic activity shocks; *OCDS* is the oil consumption demand shocks; *OCDS* is the oil inventory demand shocks; while *OSS* is the oil supply shocks.

Among the four oil shock proxies, we find only oil consumption demand shocks to have positive average returns and the highest level of deviation from its mean. The oil shocks are mostly negatively skewed except for oil inventory demand shocks; while we find all to exhibit feats of excess kurtosis. The computed absolute coefficient of variation reveals oil consumption demand shocks as the most volatile oil shock series (see results in Table 1). The mixed frequency of the summarized data calls for a methodology that adequately accommodates mixed data frequencies in one framework, without loss of data due to data aggregation of disaggregation bias. The GARCH-MIDAS framework is herein employed, given that our study involves a daily (high frequency) response variable and a monthly (low frequency) predictor variable.

In probing the data further, we conduct formal tests for volatility, autocorrelation, and higher-order autocorrelation using the Autoregressive Conditional Heteroscedasticity (ARCH) test, Q-statistic, and Q^2 –statistic, respectively; at lags 1, 5, 10, and 20 (see Table 2). All the green investments' returns are volatile, given the statistically significant ARCH test results at a 1% level, across the four specified lags. The observed volatile nature of the green investments' returns suggests that a GARCH-based modelling framework would be appropriate. On the oil shock proxies, we find economic activity shocks (significant at 1% level) and oil consumption demand shocks (significant at 10% level under lag 20 only) to exhibit conditional heteroscedasticity features at higher lags. The insignificance of the ARCH effect with respect to most of the oil shock proxies is not unexpected, given that the data frequency is relatively low. While the returns on green investments are mostly serially correlated, especially at higher lags; only oil supply shocks and economic activity shocks (higher-order autocorrelation) showed evidence of being serially correlated, at 1% level. Following from the observed data characteristics, we, therefore, employ a GARCH–MIDAS construct to examine the nexus between green investment returns and oil shocks, while also generate the volatility of green investments from its modified returns equation in (1).

Table 2: Pre-tests

Statistics	EAS	OCDP	OIDS	OSS	SPGRSLL	SPGRBND	MSGLAEL	MSGLPPL	MSGLGBL
ARCH(1)	1.25	2.14	0.08	0.66	131.87***	53.34***	185.34***	47.78***	52.99***
ARCH(5)	8.90***	1.32	0.61	0.23	189.20***	70.71***	152.25***	69.67***	114.22***
ARCH(10)	5.03***	0.63	0.70	0.18	105.13***	44.34***	82.28***	36.82***	64.75***
ARCH(20)	2.77***	1.58*	1.03	0.94	54.73***	24.00***	43.75***	21.13***	32.76***
Q(1)	0.00	0.05	0.01	0.00***	0.08	0.00	0.12	0.01	0.47
Q(5)	5.96	2.63	2.17	1.99***	24.21***	7.88	11.98**	6.75	35.29***
Q(10)	8.55	6.68	6.71	6.41***	37.06***	21.70**	34.66***	22.81**	46.30***
Q(20)	12.93	15.21	22.70	12.94***	42.24***	33.34**	48.92***	32.33**	67.73***
$Q^2(1)$	1.30	2.20	0.07	0.69***	126.21***	52.45***	174.28***	47.08***	52.12***
$Q^2(5)$	38.18***	7.52	2.25	1.32***	1182.30***	459.29***	1253.90***	405.95***	784.56***
Q^2 (10)	38.70***	8.20	5.29	2.49***	1484.70***	856.80***	1821.10***	474.30***	1169.10***
Q^2 (20)	38.83***	20.77	16.75	3.18***	1550.50***	1280.30***	2065.40***	690.18***	1330.20***

Note: ***, ** and * indicate significance of tests at 1%, 5% and 10% levels, respectively. *SPGRSLL* is the S&P Green bond select index; *SPGRBND* is the S&P Green bond index; *MSGLAEL* is the MSCI global alternative energy index; *MSGLPPL* is the MSCI global pollution prevention index; *MSGLGBL* is the MSCI global green building index; *EAS* is the economic activity shocks; *OCDS* is the oil consumption demand shocks; *OCDS* is the oil inventory demand shocks; while *OSS* is the oil supply shocks.

4. Predictions of oil shocks for green investments' volatility

Here, we focus on ascertaining the nexus between returns on green investments and oil shocks, using the GARCH-MIDAS model framework. Essentially, we consider the effect of both aggregated and disaggregated (positive and negative) measures of all four considered monthly oil shock proxies on the volatility of daily green investments. The choice of the disaggregated positive and negative oil shocks is informed by two things: first, the suggested asymmetric nature of the data that is revealed in the skewness statistics (Table 1) and the need to ascertain if asymmetry truly exists; and second, as a form of robustness. Hence, for each green investment's returns, three cases are considered. Case I uses aggregated oil shocks $\left(EAS,\, OCDS,\, OIDS\; and\; OSS\right)$; Case II uses disaggregated (negative) oil shocks $\left(EAS^{-},\, OCDS^{-},\, OIDS^{-}\;\; and\;\; OSS^{-}\right)$; while Case III uses disaggregated (positive) oil shocks $\left(EAS^{+},\, OCDS^{+},\, OIDS^{+}\;\; and\;\; OSS^{+}\right)$. The disaggregated positive (negative) oil shocks are obtained by pre-multiplying oil shocks with a dummy variable that assumes a value "1" when oil shocks are positive (negative) and assumes "0" when oil shocks are negative (positive). This disaggregated oil shocks data maintains the magnitude of the (positive or negative) returns rather than the restrictive dummy variable that appears to assign the value one to all positive (negative) oil shocks and zero, otherwise. We present the parameters of the GARCH–MIDAS model when aggregated (Table 3), negative (Table 4), and positive (Table 5) oil shocks are used as predictor variables for each return on green investments. On each table, there are five panels, with Panels 1 to 5 corresponding to SPGRSLL, SPGRBND, MSGLAEL, MSGLPPL, and MSGLGBL, respectively.

4.1 Predictions based on aggregated oil shocks (Case I)

Table 3 presents the parameter estimates of the GARCH – MIDAS model, which examines the predictability of oil shocks aggregate (EAS, OCDS, OIDS, and OSS) for green investments returns (SPGRSLL, SPGRBND, MSGLAEL, MSGLPPL, and MSGLGBL). The reported parameters are the unconditional mean for green investments return (μ), ARCH term (α), GARCH term (β), the MIDAS slope coefficient (θ) that indicates the stance of predictability, or otherwise, the one-parameter beta polynomial weight (w) that determines whether immediate past observations are assigned heavier weights than more distant past observations, and the long-run constant (m) of the MIDAS filter.

We find, mostly, statistically significant positive parameter estimates of the unconditional mean of green investments returns, the ARCH and GARCH terms, the one-parameter beta weight, and the long-run constant; across the five green investments returns and oil shocks combinations. There also appears to be high degrees of volatility persistence as indicated by the GARCH term (β), for all the paired oil shocks proxies (aggregate) and green investments returns. However, the observed persistence is mean reverting, given that the ARCH and GARCH terms sum to values less than unity $(\alpha + \beta < 1)$ irrespective of the aggregate oil shocks or green investments returns being considered. By implication, shocks to each of the five considered green investments would not be permanent, but require a longer decay time. Assessing the statistical significance of the slope coefficient (θ) for the incorporated exogenous variables – aggregate oil shocks, we find mixed results with respect to the green investments returns – aggregated oil shocks nexus being considered.

From Table 3, while there seems to be no predictability of economic activity shocks for green investment volatility of SPGRBND and MSGLGBL; we find aggregate economic activity shocks to negatively (positively) and significantly predict the volatility of green investments in the cases of SPGRSLL (MSGLAEL and MSGLPPL). These imply that while high aggregate economic activity shocks tend to reduce green investment volatility in SPGRSLL; it tends to increase green investment volatility in MSGLAEL and MSGLPPL. In the cases of aggregate oil consumption demand shocks, the predictability stance is consistently negative across the five green investment indices. This implies that high aggregate oil consumption demand shocks tend to reduce volatility on green investments, of all five green investments indices considered in this study. In other words, shocks to oil consumption demands are likely to lower the risks associated with the five green investments, an indication of the safe-haven properties of these green investments for oil crises that are occasioned by oil consumption demand.

Aggregate oil inventory demand shocks do not seem to have predictability for most of the considered green investments indices, as we only find the predictability of aggregate oil inventory demand shocks for MSGLPPL to be significantly positive. By implication, aggregate oil inventory demand shocks appear to aggravate green investments volatility of MSGLPPL. The oil price crisis that is driven by oil inventory demand tends to heighten the uncertainty associated with investing in MSGLPPL, while other green investments are not sensitive to shocks occasioned by oil inventory demands. For aggregate oil supply shocks, the predictability stance is consistently positive across the five green investment indices, given that the estimated slope coefficient for the incorporated variable, aggregate oil supply shocks, is statistically significant; which implies that aggregate oil supply shocks increase the volatility on green investments, of all the five green investments indices considered in this study. The level of uncertainty in green investment markets is heightened whenever the oil crisis is supply-driven. Put differently, green investments become riskier whenever oil supplies are in surplus and consequently leading to a crash in global oil prices; with a clear indication that all the green investments respond to events in the oil sector.

From the foregoing, our results reveal negative (for aggregate oil consumption demand shocks) and positive (for aggregate oil supply shocks) predictive stances of aggregate oil shocks for green investments volatility; and mixed signs for the coefficient of aggregate oil shocks for green investments volatility when aggregate economic activity shocks and aggregate oil inventory demand shocks were considered.

Table 3: Results of GARCH-MIDAS for oil shocks (Case I)

Parameters	EAS	OCDS	OIDS	OSS
		S&P Green bond select index (SPGRSLL)		
μ	0.0026^{**} [0.0012]	0.0025^{**} [0.0012]	0.0026^{**} [0.0012]	0.0023^{*} [0.0012]
α	0.0907^{***} [0.0096]	0.0865^{***} [0.0089]	0.0879^{*} [0.0081]	0.0664^{***} [0.0066]
β	0.8567^{***} [0.0161]	0.8695^{***} [0.0147]	0.8789^{***} [0.0129]	0.9160^{***} [0.0092]
θ	-9.0312^{***} [2.8829]	-0.8879^{***} [0.2655]	-0.4022 [0.5844]	0.5655^{***} [0.1969]
w	1.0846^{***} [0.2284]	1.3309^{**} [0.5766]	15.6920 [34.4720]	29.1300^{*} [15.5980]
m	0.0033^{***} [0.0004]	0.0041^{***} [0.0003]	0.0043^{***} [0.0004]	0.0046^{***} [0.0006]
		S&P Green bond index (SPGRBND)		
μ	0.0003 [0.0025]	0.0004 [0.0025]	0.0003 [0.0025]	0.0002 [0.0025]
α	0.0570^{***} [0.0046]	0.0512^{***} [0.0045]	0.0557^{***} [0.0044]	0.0508^{***} [0.0045]
β	0.9320^{***} [0.0063]	0.9399^{***} [0.0061]	0.9338^{***} [0.0060]	0.9342^{***} [0.0070]
θ	0.7022 [2.6902]	-0.7649^{**} [0.3202]	1.1244 [1.2745]	19.2730^{***} [4.1459]
w	16.9010 [80.7600]	48.7120 [33.6770]	49.8620 [104.8300]	1.0016^{***} [0.1730]
m	0.0214^{***} [0.0029]	0.0220^{***} [0.0033]	0.0217^{***} [0.0030]	0.0218^{***} [0.0022]
		MSCI global alternative energy index (MSGLAEL)		
μ	0.0234^{***} [0.0082]	0.0249^{***} [0.0085]	0.0237^{***} [0.0085]	0.0242^{***} [0.0084]
α	0.1097^{***} [0.0085]	0.0959^{***} [0.0075]	0.1067^{***} [0.0082]	0.1026^{***} [0.0079]
β	0.8782^{***} [0.0094]	0.8923^{***} [0.0085]	0.8822^{***} [0.0090]	0.8871^{***} [0.0087]
θ	74.9380^{*} [39.7500]	-32.0430^{***} [11.3760]	50.2080 [36.1230]	41.2300^{***} [13.2050]
w	22.5340 [20.7430]	30.4990^{**} [12.1530]	49.9880 [68.6560]	49.9860^{*} [26.7680]
m	0.4090^{***} [0.0972]	0.3745^{***} [0.0818]	0.4236^{***} [0.1051]	0.4103^{***} [0.1036]
		MSCI global pollution prevention index (MSGLPPL)		
μ	0.0271^{***} [0.0093]	0.0278^{***} [0.0093]	0.0262^{***} [0.0093]	0.0272^{***} [0.0092]
α	0.0568^{***} [0.0043]	0.0350^{***} [0.0036]	0.0534^{***} [0.0044]	0.0481^{***} [0.0041]

β	0.9363*** [0.0050]	0.9606*** [0.0043]	0.9385*** [0.0054]	0.9466*** [0.0047]
θ	36.2250** [17.6310]	-42.1620*** [10.2250]	95.4440*** [34.1110]	111.1200** [44.3860]
w	35.9300 [24.4860]	14.9830*** [3.1927]	18.2460** [8.7803]	6.2799*** [1.9473]
m	0.3609*** [0.0769]	0.3323*** [0.0643]	0.3529*** [0.0615]	0.3575*** [0.0767]
MSCI global green building index (MSGLGBL)				
μ	0.0236*** [0.0056]	0.0225*** [0.0056]	0.0231*** [0.0056]	0.0237*** [0.0056]
α	0.1521*** [0.0093]	0.1537*** [0.0122]	0.1522*** [0.0094]	0.1483*** [0.0092]
β	0.8373*** [0.0109]	0.8039*** [0.0180]	0.8375*** [0.0108]	0.8413*** [0.0105]
θ	62.3630 [49.2970]	-70.3840*** [9.5614]	52.1300 [34.4580]	28.7260** [12.5490]
w	20.2150 [23.1320]	1.0010*** [0.1371]	49.9860 [59.8110]	49.9980 [37.7010]
m	0.3143*** [0.0910]	0.1550*** [0.0142]	0.3283*** [0.0977]	0.3019*** [0.0876]

Note: Figures are the estimated coefficients and associated standard errors of GARCH-MIDAS model parameters for modelling green investment volatility in a rolling window framework that incorporates four different oil shocks proxies; presented separately in five panels titled "S&P Green bond select index", "S&P Green bond index", "MSCI global alternative energy index", "MSCI global pollution prevention index" and "MSCI global green building index". EAS – Economic activity shocks; OCDS – Oil consumption demand shocks; OIDS – Oil inventory demand shocks; and OSS – Oil supply shocks. The parameters - μ is the unconditional mean for green investments return, α is the ARCH term and β is the GARCH term, θ is the MIDAS slope coefficient that indicates the stance of predictability, w is the one-parameter beta polynomial weight, and m is the long-run constant term. ***, ** and * indicate significance of tests at 1%, 5% and 10% levels, respectively.

4.2 Predictions based on negative oil shocks

The results for parameter estimates of the GARCH – MIDAS model, which tests the predictability of negative oil shocks $\left(EAS^{-}, OCDS^{-}, OIDS^{-} \; and \; OSS^{-}\right)$ for green investments returns (SPGRSLL, SPGRBND, MSGLAEL, MSGLPPL, and MSGLGBL) is presented in Table 4. The reported parameters remain as previously defined. The parameter estimates of the unconditional mean for green investments returns, the ARCH and GARCH terms, the one-parameter beta weight, and the long-run constant; across the five green investments' returns and negative oil shocks combinations are positive and mostly statistically significant, with feats that are quite similar to the case of the aggregate oil shocks in Case I (especially for the oil supply shocks). There observed volatility persistence is very high, as evidenced by the GARCH term (β) across the negative oil shocks proxies and green investments returns. And in the similitude of the case of aggregate oil shocks, the persistence in each case is, however, mean-reverting, since $\alpha+\beta<1$, irrespective of the negative oil shocks or green investments returns being considered. Imperatively, shocks to green investments would not be permanent, but may only require a longer decay time. The MIDAS filter specified slope coefficient (θ) associated with the exogenous variable – negative oil shocks measure the response of how green investments volatility to negative oil shocks. We herein find mixed stances of predictability that are green investment returns – negative oil shocks nexus dependent.

From the results in Table 4, we find no stance of predictability of negative economic activity shocks for green investment volatility of MSGLGBL, a similitude of the aggregate economic activity shocks. However, negative economic activity shocks seem to predict green investment volatility significantly negatively in the case of SPGRBND but predict green investment volatility significantly positively in the cases of SPGRSLL, MSGLAEL, and MSGLPPL. Negative oil consumption demand shocks were found to predict green investment volatility significantly positively (SPGRSLL) and negatively (MSGLAEL, MSGLPPL, and MSGLGBL); while no predictability was found for SPGRBND. The predictability stance of negative oil inventory demand shocks for green investment volatility in the case of SPGRSLL was significantly positive; while the predictability of negative oil supply shocks for green investment volatility did not differ from the aggregate oil supply shocks. The results in Table 4 show positive (for oil supply shocks) predictive stances of negative oil shocks for green investments volatility; and mixed predictability of negative oil shocks for green investments volatility in the cases of economic activity shocks, oil consumption demand shocks, and oil inventory demand shocks. Clearly, oil supply shocks and economic activities drive green investments' uncertainties higher, while demand-driven oil shocks cause uncertainty in the green investment market to drop.

Table 4: Results of GARCH-MIDAS for negative oil shocks (Case II)

Parameters	EAS^{-}	$OCDS^{-}$	$OIDS^{-}$	OSS^{-}
		S&P Green bond select index (SPGRSLL)		
μ	0.0027** [0.0012]	0.0027** [0.0012]	0.0025** [0.0012]	0.0026** [0.0012]
α	0.0908*** [0.0081]	0.0945*** [0.0087]	0.0896*** [0.0080]	0.0870*** [0.0102]
β	0.8656*** [0.0139]	0.8568*** [0.0153]	0.8713*** [0.0132]	0.8369*** [0.0195]
θ	6.0968* [3.4571]	1.3981*** [0.5167]	6.9075* [3.5454]	6.0805*** [0.9372]
w	1.0035* [0.5958]	2.2413 [1.5864]	1.2169** [0.5216]	2.5931*** [0.6702]
m	0.0029*** [0.0007]	0.0022*** [0.0007]	0.0021* [0.0011]	0.0016*** [0.0003]
		S&P Green bond index (SPGRBND)		
μ	0.0005 [0.0025]	0.0003 [0.0025]	0.0003 [0.0025]	0.0005 [0.0025]
α	0.0539*** [0.0039]	0.0561*** [0.0044]	0.0560*** [0.0043]	0.0476*** [0.0042]
β	0.9381*** [0.0052]	0.9336*** [0.0060]	0.9345*** [0.0061]	0.9437*** [0.0059]
θ	-4.4425** [1.9047]	-0.3295 [0.5278]	-4.9682 [15.8990]	9.6174*** [3.2073]
w	49.9760 [51.6650]	49.9640 [137.3900]	4.6137 [15.4990]	37.0970** [16.8970]
m	0.0243*** [0.0042]	0.0222*** [0.0034]	0.0237*** [0.0067]	0.0174*** [0.0025]
		MSCI global alternative energy index (MSGLAEL)		
μ	0.0243*** [0.0084]	0.0249*** [0.0083]	0.0235*** [0.0084]	0.0247*** [0.0085]
α	0.1140*** [0.0099]	0.1062*** [0.0085]	0.1047*** [0.0080]	0.0983*** [0.0075]
β	0.8600*** [0.0122]	0.8759*** [0.0099]	0.8854*** [0.0086]	0.8917*** [0.0082]
θ	1386.1000*** [337.3700]	-178.2600*** [62.6650]	-297.7900 [207.8100]	287.6300*** [91.6000]
w	1.0225*** [0.2040]	2.5772** [1.1274]	6.7522 [4.8284]	49.9910*** [18.3510]
m	0.0272 [0.0528]	0.6043*** [0.1344]	0.5248*** [0.1571]	0.2884*** [0.0734]
		MSCI global pollution prevention index (MSGLPPL)		
μ	0.0279*** [0.0093]	0.0282*** [0.0093]	0.0266*** [0.0093]	0.0288*** [0.0092]
α	0.0642*** [0.0059]	0.0485*** [0.0038]	0.0544*** [0.0045]	0.0399*** [0.0043]
β	0.9196*** [0.0085]	0.9453*** [0.0045]	0.9394*** [0.0052]	0.9543*** [0.0049]
θ	552.8300*** [126.9200]	-57.1510** [22.7710]	58.8880 [48.1220]	278.5000*** [64.6100]
w	7.8402*** [2.1439]	9.5338* [5.0364]	39.9700 [58.4810]	24.4470*** [5.4258]
m	0.1785*** [0.0300]	0.4275*** [0.0891]	0.3479*** [0.0763]	0.2101*** [0.0392]
		MSCI global green building index (MSGLGBL)		
μ	0.0235*** [0.0056]	0.0226*** [0.0056]	0.0231*** [0.0056]	0.0241*** [0.0056]
α	0.1529*** [0.0094]	0.1528*** [0.0101]	0.1513*** [0.0091]	0.1309*** [0.0090]
β	0.8367*** [0.0110]	0.8184*** [0.0136]	0.8405*** [0.0102]	0.8624*** [0.0096]
θ	79.2290 [127.8700]	-140.4300*** [28.1720]	118.4900 [95.3670]	248.4900** [101.7300]
w	28.1230 [63.1090]	1.0010*** [0.2084]	49.9980 [66.6910]	37.3450** [18.6430]
m	0.2965*** [0.0930]	0.3861*** [0.0572]	0.3346*** [0.1132]	0.2587*** [0.0984]

Note: Figures are the estimated coefficients and associated standard errors of GARCH-MIDAS model parameters for modelling green investment volatility in a rolling window framework that incorporates four different oil shocks proxies; presented separately in five panels titled "S&P Green bond select index", "S&P Green bond index", "MSCI global alternative energy index", "MSCI global pollution prevention index" and "MSCI global green building index". EAS – Economic activity shocks; OCDS – Oil consumption demand shocks; OIDS – Oil inventory demand shocks; and OSS – Oil supply shocks. The parameters - μ is the unconditional mean for green investments return, α is the ARCH term and β is the GARCH term, θ is the MIDAS slope coefficient that indicates the stance of predictability, w is the one-parameter beta polynomial weight, and m is the long-run constant term. ***, ** and * indicate significance of tests at 1%, 5% and 10% levels, respectively.

4.3 Predictions based on positive oil shocks

We follow the pattern of discussion as earlier presented for aggregate and negative oil shocks. Table 5 shows the results for parameter estimates of the GARCH – MIDAS model, which measures the predictability of positive oil shocks $\left(EAS^{+}, OCDS^{+}, OIDS^{+}\ and\ OSS^{+}\right)$ for green investments volatility (SPGRSLL, SPGRBND, MSGLAEL, MSGLPPL, and MSGLGBL), with the reported parameters remaining as previously defined. As with previous cases, all the parameter estimates of the unconditional mean for green investments returns, the ARCH and GARCH terms, the one-parameter beta weight, and the long-run constant; across the five green investments, returns and positive oil shocks combinations are positive and mostly statistically significant, with feats that are quite similar to the case of the aggregate oil shocks in Case I (especially for the oil consumption demand shocks). We also observe volatility persistence to be high, transient and mean-reverting, given that $\alpha + \beta < 1$, irrespective of the positive oil shocks or green investments indices. The slope parameter (θ) associated with positive oil shocks gives an insight as to how green investment volatility responds to positive oil shocks. Our predictability results are mixed for the different green investment indices under the incorporation of positive oil shocks (except for positive oil consumption demand shocks). Across the green investment indices, positive oil consumption significantly and negatively predicts green investment volatility, while the remaining positive oil shocks mostly predicted green investment volatility significantly positively. Again, green investments' uncertainties are aggravated mostly by shocks emanating from oil supply and economic activities, while a shock to oil demand for consumption tends to lead to lower uncertainty in the green investment markets.

Another interesting feat that can be drawn from the above results (positive oil shocks), when compared to results in Case II (negative oil shocks) is the stance of the asymmetry effect. Negative oil supply shocks align with aggregate oil supply shocks, in terms of sign and significance; while in a similar pattern, positive oil consumption demand shocks align with aggregate oil consumption demand shocks. Imperatively, aggregate oil supply shocks and aggregate oil consumption demand shocks are majorly driven by negative oil supply shocks and positive oil consumption demand shocks, respectively. There are, however, several evidenced differences in the responses of green investment volatility to negative and positive oil shocks, which is an indication of the relevance of accounting for asymmetry in oil shocks when modelling green investment volatility – oil shocks nexus. Negative and positive oil shocks do not have the same impact on the volatility of green investments. It would be better to model these negative and positive oil shocks separately, rather than aggregating both as a single series.

Table 5: Results of GARCH-MIDAS for positive oil shocks

Parameters	EAS^{+}	$OCDS^{+}$	$OIDS^{+}$	OSS^{+}
	S&P Green bond select index (SPGRSLL)			
μ	0.0027** [0.0012]	0.0026** [0.0012]	0.0026** [0.0012]	0.0027** [0.0012]
α	0.0907*** [0.0102]	0.0918*** [0.0098]	0.0880*** [0.0080]	0.0950*** [0.0089]
β	0.8430*** [0.0176]	0.8319*** [0.0191]	0.8787*** [0.0128]	0.8563*** [0.0160]
θ	-6.1816*** [1.4093]	-1.5688*** [0.2722]	-0.4931 [0.9015]	-1.6619** [0.7436]
w	2.4734*** [0.9035]	1.4204*** [0.3869]	16.4360 [54.4460]	2.4451 [2.4171]
m	0.0021*** [0.0004]	0.0017*** [0.0004]	0.0041*** [0.0005]	0.0034*** [0.0004]
	S&P Green bond index (SPGRBND)			
μ	0.0004 [0.0025]	0.0003 [0.0025]	0.0003 [0.0025]	0.0004 [0.0025]
α	0.0584*** [0.0045]	0.0463*** [0.0042]	0.0563*** [0.0043]	0.0508*** [0.0037]
β	0.9307*** [0.0063]	0.9456*** [0.0058]	0.9332*** [0.0059]	0.9427*** [0.0048]
θ	4.5358 [3.0885]	-2.1183*** [0.7304]	0.6115 [2.2170]	10.6130* [5.7714]
w	15.6700 [15.4240]	31.9940* [17.4900]	25.9750 [191.5100]	3.2236* [1.7387]
m	0.0232*** [0.0034]	0.0185*** [0.0026]	0.0218*** [0.0033]	0.0301*** [0.0069]
	MSCI global alternative energy index (MSGLAEL)			
μ	0.0233*** [0.0082]	0.0238*** [0.0085]	0.0238*** [0.0085]	0.0240*** [0.0084]
α	0.1071*** [0.0081]	0.0941*** [0.0077]	0.1049*** [0.0081]	0.1050*** [0.0080]
β	0.8825*** [0.0087]	0.8951*** [0.0086]	0.8836*** [0.0089]	0.8847*** [0.0089]
θ	80.8700* [41.6410]	-56.2160*** [19.5910]	100.5200* [52.5050]	40.8590*** [15.1560]
w	24.4030 [23.6420]	49.9940** [25.3680]	49.9820 [45.2530]	49.9810 [38.3780]
m	0.4488*** [0.1152]	0.2981*** [0.0689]	0.4518*** [0.1111]	0.4365*** [0.1120]
	MSCI global pollution prevention index (MSGLPPL)			
μ	0.0271*** [0.0093]	0.0272*** [0.0093]	0.0275*** [0.0092]	0.0272*** [0.0093]
α	0.0564*** [0.0044]	0.0337*** [0.0042]	0.0554*** [0.0046]	0.0513*** [0.0041]
β	0.9373*** [0.0049]	0.9607*** [0.0052]	0.9319*** [0.0064]	0.9436*** [0.0049]
θ	39.1640** [19.9110]	-86.5800*** [18.2680]	269.6900*** [85.8440]	103.1100 [65.2970]
w	39.8880 [29.3480]	19.7020*** [3.7218]	4.6593** [1.8269]	4.8127* [2.8830]
m	0.3800*** [0.0857]	0.1863*** [0.0329]	0.4291*** [0.0641]	0.4184*** [0.1074]
	MSCI global green building index (MSGLGBL)			
μ	0.0235*** [0.0056]	0.0233*** [0.0056]	0.0226*** [0.0057]	0.0236*** [0.0056]
α	0.1508*** [0.0091]	0.1426*** [0.0093]	0.1568*** [0.0108]	0.1511*** [0.0093]
β	0.8395*** [0.0105]	0.8483*** [0.0104]	0.8197*** [0.0143]	0.8384*** [0.0106]
θ	76.7580 [55.3210]	-34.4880* [18.0070]	324.1700*** [81.8200]	27.8700* [15.0390]
w	18.5750 [21.6720]	49.9740 [43.1500]	1.1574*** [0.3046]	49.9900 [54.0850]
m	0.3492*** [0.1075]	0.2699*** [0.0880]	0.3565*** [0.0626]	0.3190*** [0.0936]

Note: Figures are the estimated coefficients and associated standard errors of GARCH-MIDAS model parameters for modelling green investment volatility in a rolling window framework that incorporates four different oil shocks proxies; presented separately in five panels titled "S&P Green bond select index", "S&P Green bond index", "MSCI global alternative energy index", "MSCI global pollution prevention index" and "MSCI global green building index". EAS – Economic activity shocks; OCDS – Oil consumption demand shocks; OIDS – Oil inventory demand shocks; and OSS – Oil supply shocks. The parameters - μ is the unconditional mean for green investments return, α is the ARCH term and β is the GARCH term, θ is the MIDAS slope coefficient that indicates the stance of predictability, w is the one-parameter beta polynomial weight, and m is the long-run constant term. ***, ** and * indicate significance of tests at 1%, 5% and 10% levels, respectively.

5. Concluding remarks

In this paper, we analyze the effect of oil shock variants on the green investments' volatility, drawing from Baumeister and Hamilton's (2019) demand- and supply-based decomposed oil shock components: economic activity shocks, oil consumption demand shocks, oil inventory demand shocks, and oil supply shocks. We examine the green investments' volatility – oil shocks nexus using the GARCH - MIDAS regression framework that allows for mixed variable frequencies within one predictive model; especially, considering the nature of our variables of interest that are monthly (low) frequency predictors (oil shocks) and daily (high) frequency response variable (green investments' volatility). Data spanning September 2010 to June 2021 are analyzed; with oil shocks being further disaggregated into positive and negative shocks in a bid to investigate the possible asymmetry effect on green investments' predictability by oil shocks.

Findings in this paper indicate both homogeneity (OCDS and OSS) and heterogeneity (EAS and OIDS) in the predictability of aggregate oil shocks for green investments' volatility. Aggregate oil consumption demand shocks tend to reduce volatility while aggregate oil supply shocks tend to increase the volatility on all green investments considered in this paper. For aggregate economic activity and aggregate oil inventory demand shocks, results of the predictability are mixed/heterogeneous. The alternate predictive relationships associated with the demand- and supply-driven shocks are indications of the sensitivity of green investments' volatility to oil shocks; which aligns with the stance in Park et al. (2020); while the stance of heterogeneity in the response of green investments to oil shocks aligns with Salisu and Gupta (2020). Upon disaggregating oil shocks into negative shocks, and in the case of oil supply shocks, there are positive predictive stances of negative oil supply shocks for green investments' volatility indicating homogeneity in the response of green investments' volatility to negative oil supply shocks, while predictive stances of the volatility of green investments are mixed/heterogeneous in the cases of economic activity shocks, oil consumption demand shocks, and oil inventory demand shocks. For positive oil shocks, heterogeneity in predictability also persists across the five green investments for all oil shocks except for positive oil consumption demand shocks. By comparing the results of positive and negative oil shocks with that of aggregate oil shocks, we find negative oil supply shocks to align with aggregate oil supply shocks in terms of sign and significance, while positive oil consumption demand shocks align with aggregate oil consumption demand shocks. Consequently, aggregate oil supply shocks and aggregate oil consumption demand shocks are majorly driven by negative oil supply shocks and positive oil consumption demand shocks. However, the predictability of the negative and positive oil shocks for green investments' volatility differ markedly, an indication of the asymmetry effect. This result also aligns with extant studies (Dutta et al., 2020; Lee et al., 2020; among others) that show the feat of switching regimes when modelling the nexus between oil shocks and green investment volatility.

The implication of our findings is the necessity for optimizing green investment portfolio strategies amidst oil shocks of different impacts. Besides, predictions of the volatility of green investments by demand-related (consumption and inventory) oil shocks could yield a differential capacity for raising precautionary demand to forestall stability in the future supply of oil. Finally, the findings will be of interest to green investment market participants as it informs them of sources of oil-related shocks to their investments.

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