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Are oil-clean energy and high technology stock prices in the same straits? Bubbles speculation and time-varying perspectives

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A B S T R A C T

Motivated by the drive to improve the performance and growth of clean energy technology amidst related high-tech innovations, the vulnerability of clean energy and high-tech stock prices to oil shocks is examined, by illustrating the potential bubbles and time-varying interactions among the commodities over the period from January 2004 to December 2017. In this regard, we contribute to the literature in two aspects. First, we analyze an empirically important issue with the SADF (Supremum Augmented Dickey-Fuller) approach for explosive bubbles in oil price, clean energy, and high-tech stock prices. Second, the Markov Chain Monte Carlo (MCMC) approach of the Bayesian time-varying parameter Vector Autoregressions model with stochastic volatility (TVP-SVAR) technique is used to account for time-varying and state dependent interactions between commodities. We found that the time varying behavior of the dependence among clean energy, high technology stocks and oil prices is mainly due to major bubbles identified in the underlying series. We established contrasting evidence between the responses of clean energy and high-tech stocks to oil disruption shocks. Moreover, the stock return volatilities of high technology stocks have no effect on investors' expectations of clean energy returns across different time horizons. Overall, this study presents significantly relevant policy guideline.

1. Introduction

In reality, the development of alternative and clean energy sources has increasingly become opened up the dynamism of the 21st century energy market largely because of the enormous challenges associated with the global climate change and the century's default for technological advancement. For instance, the Bloomberg New Energy Outlook 2019 clearly outlined the development of alternative energy sources and the subsequent rate of acceleration of the energy mix by 2030 and 2050 [1]. The global energy generation from renewables (mainly from solar, wind, and hydro) by 2050 is forecasted at 62% of total energy output, a reduction to 31% fossil fuels by 2050 (mainly from oil, coal, and gas), and 7% nuclear energy by 2050 [2,36]. In achieving this milestone (attaining a 12tetra watt energy generation capacity by 2050), the report of the Bloomberg New Energy Outlook 2019 opined an expected renewable energy generation of 77% share of total energy generation through a potential $13.3 trillion investments in technological innovations and renewable energy sources by 2050. One way to make such a large investment in clean energy and high technology sectors is through capital markets. This suggests that companies engaged in these sectors should be successfully traded on the stock markets. However, investors need more information on the dynamics of the stocks in these markets in order to gain better understanding of clean energy and high technology markets.

In theory, international oil price movements have been considered as major energy-related risks that positively impact the financial performance of renewable energy and high-tech companies. This link is rooted in the substitution effect of renewable energy and technology innovation on traditional fossil fuels, especially oil. Specifically, an increase in oil prices boosts the demand for green energy, and investors shift their portfolios into green energy firms. As a result, clean energy stock returns would

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increase. This substitution effect has been largely evidenced in the literature (Apergis and Payne, 2014 [3]; Managi and Okimoto, 2013; Reboredo, 2015; Reboredo et al., 2017), while a small number of researchers find that the substitution effect between oil and clean energy is not significant [4]; Troster et al., 2018).

Further evidence has also indicated the role of technology companies in the development of clean energy companies since clean energy companies channel volatility to technology companies, and this link is reinforced by oil shocks (Tiwari et al., 2021). Based on this narrative, technology firms would engage in research and development activities in face of higher oil prices in order to expand alternative energy innovation sources, and thus their stock appreciate (Bondia et al., 2016). Similarly, oil price increases can directly influence technology stock returns by raising the costs of the transportation component of e-business (Managi and Okimoto, 2013; [5]. In contrast, some authors demonstrate a weak contribution of oil prices to technology companies mainly because technology companies involve in business activities that are not very energy intensive [6], whereas several studies demonstrate that the stock prices of clean energy companies are relatively highly correlated with the stock prices of high technology companies (Inchauspe et al., 2015 [7]; Kumar et al., 2012; [5,8]. In this light, it could be argued that the literature on linkages between oil prices and stock prices of green energy and high technology companies are inconclusive.

The motivation of this study typically follows the renewed interest in identifying the optimal mix of green energy and high-tech investment to address the global energy security and environmental sustainability issues. Another additional motivation of this study draws on the lack of rigorous analysis on inter-relationships between oil prices, high technology, and clean energy in a time-varying VAR framework. Priors works usually employed cointegration techniques, multivariate GARCH and dynamic conditional correlation (DCC) models (see e.g. Bondia et al., 2016; [7], while relatively few studies use a vector autoregression model [4]; Kumar et al., 2012; Managi and Okimoto, 2013). These econometric techniques generally describe the size and direction of the correlation between variables. Moreover, the time-varying correlations between clean energy, high technology stock markets and oil prices at different horizons have been neglected in previous studies.

Considering the aforementioned motivations, the current study attempts to examine the interactions among the global oil prices and the stock prices of high-tech and clean energy. With the objective of examining potential bubbles and time-varying interactions between the global oil prices, high-tech and clean energy stock prices, we posit the significance and novelty of the current study in from two main perspectives. Foremost, the current study implement the Markov Chain Monte Carlo (MCMC) approach of the Bayesian time-varying parameter Vector Autoregressions model with stochastic volatility (TVP-SVAR) to provide the time varying relationship between the commodity prices, thus providing a significant deviation from the study of Sadorsky [5]. In addition, by providing evidence of potential bubbles among the examined variables, and especially from the global perspective, the current study expectedly expand the scope of the existing related literature.

In order to provide a clear outline for the readership of this study, the succeeding sections are carefully presented in a unique format. The methodology of the study is presented in section 2, Data and univariate analysis are outlined in section 3. The estimation results are presented in section 4. Section 5 discusses the empirical findings while conclusion and policy guideline from the study are captured in section 6.

2. Theoretical concept

As detailed in the 1930's creative destruction work of Schumpeter, the role of innovation management is suggestively central to economic development and recovery [9]. The study linked the availability of the financial institution's credit-driven fund to the investment opportunities especially in innovation, thus supporting the hypothesis of positive nexus between finance (financial system) and innovation. Considering that profit or loss could be accrued to sectors of the economy, depending on the specificity of the industry, the oil price dynamic is related to (i) the aspect of stock prices as a financial instrument, and (ii) clean energy sources from the substitution effect perspective. Considering that the development of alternative energy is a function of innovation and climate-related issues, Henriques and Sadorsky [4] specifically examined the stock prices technology, alternative energy, and oil prices. Moreover, while Sadorsky [6] offered a relevant insight to the determinants of technology price volatility, a handful studies such as Sadorsky [5] and Kocaarslan and Soytas [7] further provided an expansion of the 1930's work of Schumpeter's creative destruction.

2.1. Methodology

We adopt the Bayesian time-varying parameter Vector Autoregression model with stochastic volatility (TVP-SVAR) to assess the co-movements between oil prices, clean energy, and high technology stock returns. In order to give reader an insight about the TVP-SVAR model, we follow [10] and specify the VAR model with time-varying parameters as below:

$$z_t = a_t + B_{1,t}z_{t-1} + ... + B_{k,t}z_{t-k} + \mu_t \quad t = 1, ..., T \tag{1}$$

where a_t *and* $B_{i,t}$ (for $i = 1, .., k$) are time-varying parameters and μ_t are heteroskedastic errors with zero mean and time varying variance-covariance matrix I_t. The co-movements among oil prices, high technology and clean energy stock returns are modeled by I_t in a simple way by writing

$$I_t = A_t^{-1}\Sigma_t\Sigma_t'\left(A_t^{-1}\right)' \tag{2}$$

where A_t is a lower triangular matrix capturing all the relationships among the series simultaneously, as Equation (3):

$$A_t = \begin{pmatrix} 1 & 0 & \dots & 0 \\ \alpha_{21}, t & 1 & \dots & 0 \\ \dots & \dots & .... & 0 \\ \alpha_{s1,t} & \dots & \alpha_{s(s-1),\ t} & 1 \end{pmatrix} \tag{3}$$

and Σ_t is a diagonal matrix of the stochastic volatilities as Equation (4)

$$\Sigma_t = \begin{pmatrix} h_{1,t} & 0 & \dots & 0 \\ 0 & h_{2,t} & \dots & 0 \\ \dots & \dots & .... & 0 \\ 0 & \dots & 0 & h_{s,t} \end{pmatrix} \tag{4}$$

where $h_{i,t}$ is the standard deviation of the structural shock, for $i = 1, .., s$.

Thus, Equation (1) can be re-specified as

$$z_t = a_t + B_{1,t}z_{t-1} + ... + B_{p,t}z_{t-p} + A_t^{-1}\Sigma_t\varepsilon_t \tag{5}$$

where $\varepsilon_t \sim N(0,\ \pi_s)$, π_s is a s-dimensional identity matrix. B_t and the elements of A_t follow a random walk process. The dynamics of the parameters in Equation (5) may be specified according to the three state equations.

$$B_t = B_{t-1} + \eta_{\beta t};\ \alpha_t = \alpha_{t-1} + \eta_{\alpha t}\ ;\ \log h_t = \log h_{t-1} + \eta_{ht} \tag{6}$$

From above Equations, we observe that B_t and α_t are assumed to evolve as random walks, whereas σ_t is modeled as a geometric random walk belonging to the class of stochastic volatilities. The innovations $\{\varepsilon_t, \eta_t,\ \varepsilon_t,\ \xi_t\}$ are assumed to be jointly normal with the following variance-covariance matrix:

$$V = var\left(\begin{bmatrix} \varepsilon_t \\ \eta_{\beta t} \\ \eta_{\alpha t} \\ \eta_{ht} \end{bmatrix}\right) = \begin{bmatrix} \pi_s & 0 & 0 & \theta \\ 0 & \Sigma_\beta & 0 & 0 \\ 0 & 0 & \Sigma_\alpha & 0 \\ 0 & 0 & 0 & \Sigma_h \end{bmatrix} \tag{7}$$

where π_s, Σ_β, Σ_α, and Σ_σ are positive definite matrices. To overcome the overparameterization bias, the MCMC techniques are implemented based on Bayesian inference in evaluating the posterior distributions of the parameters of the above models.

3. Data presentation and univariate analysis

3.1. Data presentation

The analysis makes use of green energy and high technology stock indices and the oil prices. Our experimental period starts from January 2004 to December 2017 and includes a total of 168 observations. Interestingly, our experimental period covers several major events such as the global financial crisis (GFC) of 2008 and the oil price crash of 2014. Thus, as a result, it allows us to examine how the co-movements between green and high technology stock markets and oil markets were affected.[1]

The green energy and high technology stock indices are provided by the Bloomberg database. For the oil prices, we use the West Texas Intermediate (WTI) crude oil future prices as it serves as benchmark and moved closely with other crude oil baskets such as Dubai, Brent, and OPEC.

The WTI crude oil price data is derived from the Energy Information Administration (EIA) database.

The graphical representation of the series indicates that oil prices, green energy and high technology stock indices are subject to several major structural shifts during the sample period (See Fig. 1). It is evident that all the series at study show breaks during the global financial turmoil of 2008. A significant effect of the global financial crisis on oil prices, high-tech and green energy stock indices has been demonstrated by several authors [11,12]. In addition, major spikes were observed in the second half of 2014 in the temporal dynamics of oil prices and high technology stock index. These structural shifts can be accredited to the great oil bust of 2014 and its spillover effect on high technology stock markets.

Another key observation is that clean energy and high technology stock indices seem to have diverging dynamics after 2008, while the temporal dynamic of oil price seems to be more closely related to movements in clean energy stock market over the recent period, after 2014. This indicates that the existence of common patterns between clean energy stock markets and in oil prices [13,14]. However, the green energy stock index is less volatile compared to that of high technology stock index. This is understandable, given that many businesses have increased their innovation investments after the shock of 2008. It is also reported that dramatic market changes are stimulated open innovation activities after the global financial crisis [15,16]. The visual inspection indicates that the series exhibit nonstationary behavior and there is need to capture this stochastic behavior through our estimation strategy.

3.1.1. Linearity tests

As discussed earlier, we check the nonlinear behavior of the underlying series by conducting the nonlinearity tests developed by Ref. [17]. We also determine the presence of explosive breaks in the temporal dynamics of the series by testing the existence of bubble phenomena through the method proposed by Ref. [18]. As reported in Table 1, the BDS strongly support nonlinear behavior in the series as the null hypothesis of linearity is strongly rejected for all the variables at the conventional level of significance. This implies the prevalence of nonlinear dynamic in the series.

3.1.2. Bubble tests based on SADF

Furthermore, we use the SADF test to detect possible bubble phenomena in the series. As reported in Fig. 2, there is evidence of explosive behavior over different periods. Oil prices and clean energy stock index shows signs of explosive behavior and unsustainable bubble around the global financial crisis February 2008. As reported by Alola [19]; these bubbles can be accredited to the massive amount of speculative transactions before the great recession of 2008. A significant robust speculative bubble is observed in the early 2014 in high technology returns. The detection of this bubble emerges from the unexpected expansion in the shale technology causing a drastic decrease in oil prices observed in June 2014 [20,21]. Overall, both linearity/stability tests show that our underlying variables display nonlinearity with explosive processes. In this context, modelling the interaction between series without accounting for the explosive phenomena and nonlinearity would lead to wrong inferences. As a result, our estimation strategies based on the time-varying parameter with stochastic volatility VAR model is more suitable to model the co-movements between the underlying variables.

We perform several unit root tests to account for the possible structural shifts in our series (Table 2). To be more specific, the conventional augmented Dickey-Fuller (ADF) tests of [22] and the DF-GLS (generalized least squares) test of [23]. Given the low power and size distortions of these tests when the data generating process exhibits complex behavior as in our case, we perform sophisticated unit root tests able to capture a more complex nonlinear behavior in the series. In this light, we employ the flexible Fourier variant of the ADF test introduced by Ref. [24] and the structural break based ADF test proposed by Ref. [25].

3.1.3. Descriptive statistics, stochastic properties of the series and the pairwise correlation matrix

We present the summary statistics of the log-returns for each data series (Table 2). We observe that the highest average returns are observed for high-tech firms followed oil market, while green energy stock market exhibits negative average returns. However, the summary statistics of the standard deviation report that clean energy stock returns depicts the highest uncertainty while the uncertainty levels of oil and high technology returns are quite similar. As demonstrated by Ref. [26], green energy and oil returns are skewed to left with excess kurtosis, except high-tech stock returns. This implies that the evidence of negative returns is dominant in green energy and oil future markets. As expected, the J-B statistics reject the null of normality, suggesting that all the returns are not normally distributed.

Furthermore, inspecting the unit root tests (Table 2), one can conclude that all the series are stationary in first difference I (1),

[1] As shown in recent studies [7], green energy and high technology stock markets have experienced a significant amount of investments particularly after 2004 and most of previous studies focus on the period following 2004. These tendencies also motivate the choice of our sample period, restricted after 2003.

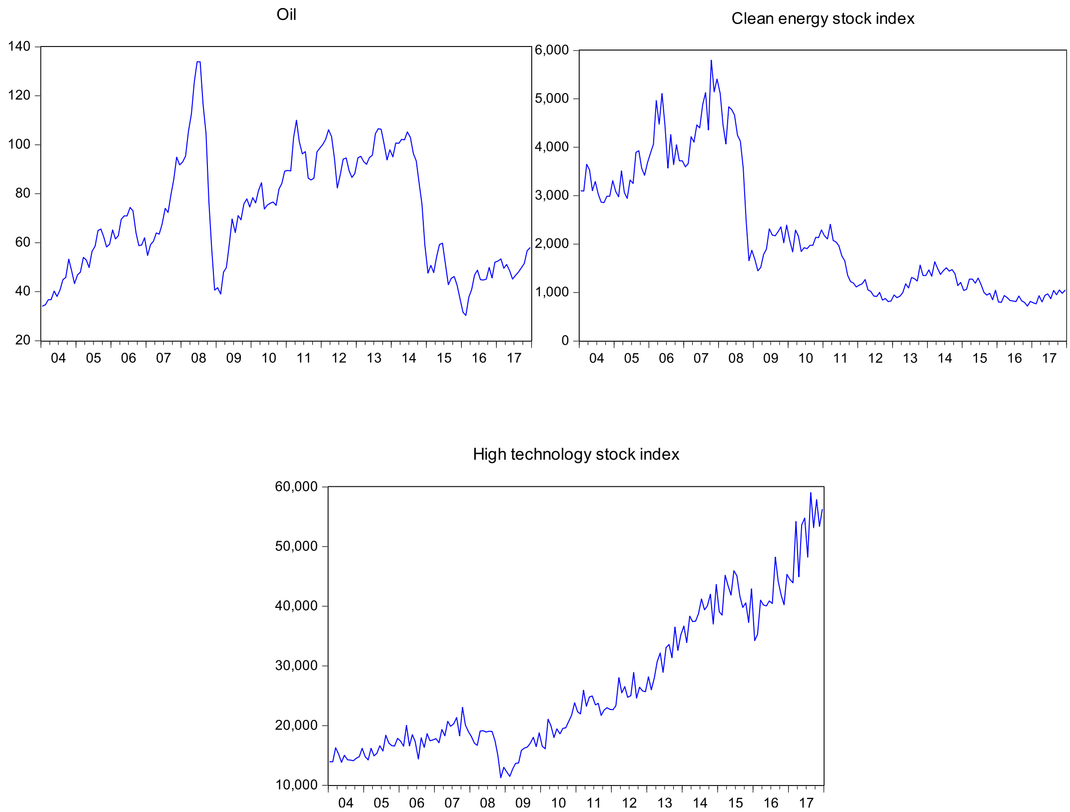

Fig. 1. Time-series plot of oil prices, clean energy stock index and high technology stock index.

Table 1
BDS linearity tests.

	OIL			ECO			PSE		
DIM	2	3	4	2	3	4	2	3	4
BDS	0.166	0.278	0.350	0.171	0.294	0.380	0.165	0.286	0.373
Z.Stat	45.560[a]	47.906[a]	50.503[a]	37.901[a]	40.602[a]	44.521[a]	35.174[a]	38.250[a]	41.847[a]
Prob.	0.000	0.000	0.000	0.000	0.000	0.000	0.000	0.000	0.000

Notes: The BDS statistic proposed by Ref. [17] is used to account for nonlinearity in the series at level. Dim. represents embedding dimension. The BDS test for an embedding dimension from 2 to 6 was used. ECO: clean energy stock index; PSE: high technology stock index, OIL: WTI oil prices.

confirming that all the return indexes show a stationary process. Therefore, we perform our analysis based on the first differences of logarithmic prices of the stock indexes and oil futures as the returns of renewable energy, high technology, and oil futures.

To complete the univariate analysis, we report the correlation matrix in Table 3. We find that high technology stock returns (PSE) are positively and strongly correlated with renewable energy stock returns. By contrast, there is a negative correlation between oil prices and clean energy returns, while a positive and weak correlation is observed between oil returns and high technology returns. The evidence of positive and strong correlation between renewable energy stock returns and high technology returns has been demonstrated by some scholars [4,26].

4. Empirical analysis

Following (J [10,27], the MCMC approach based on Bayesian inference is used to estimate the TVP-SVAR model in terms of unobserved latent variables. Based on the AIC, we find that the optimal lag length is two, then we estimate the two lags TVP-SVAR model using MCMC algorithm. The MCMC iterations are drawn 10,000 times, for which we use the multi-move sampler and discard the initial 1000 as burn-in sample for convergence. The multi-move sampler technique initially introduced by Ref. [28] is used to draw sample from the exact posterior density of the stochastic volatility. Following (Jouchi [29], we set the following priors for the *i-th* diagonals of the variance covariance matrices:

$$(\Sigma_\beta)_i^{-2} \sim G(10, 0.01),\ (\Sigma_\alpha)_i^{-2} \sim G(2, 0.01),\ (\Sigma_\sigma)_i^{-2} \sim G(2, 0.01),$$

where $(\Sigma_\alpha)_i^{-2}$ and $(\Sigma_\sigma)_i^{-2}$ are *i-th* diagonal elements of the respective Σ_α and Σ_σ matrices. G stands for Gamma distribution. For the initial states of the time-varying parameters, we set the following flat priors as: $\beta_{\mu 0} = \alpha_{\mu 0} = \sigma_{\mu 0} = 0$, and $\Sigma_{\beta 0} = \Sigma_{\alpha 0} = \Sigma_{\sigma 0} = 4 \times I$.[2]

Figure A1 reports the sample autocorrelation functions, the sample paths and posterior densities. One observation is that the sample paths seem stable, and the sample autocorrelation

[2] For more details about the estimation of the TVP-SV-VAR model, we refer interested readers to (Jouchi Nakajima et al., 2011).

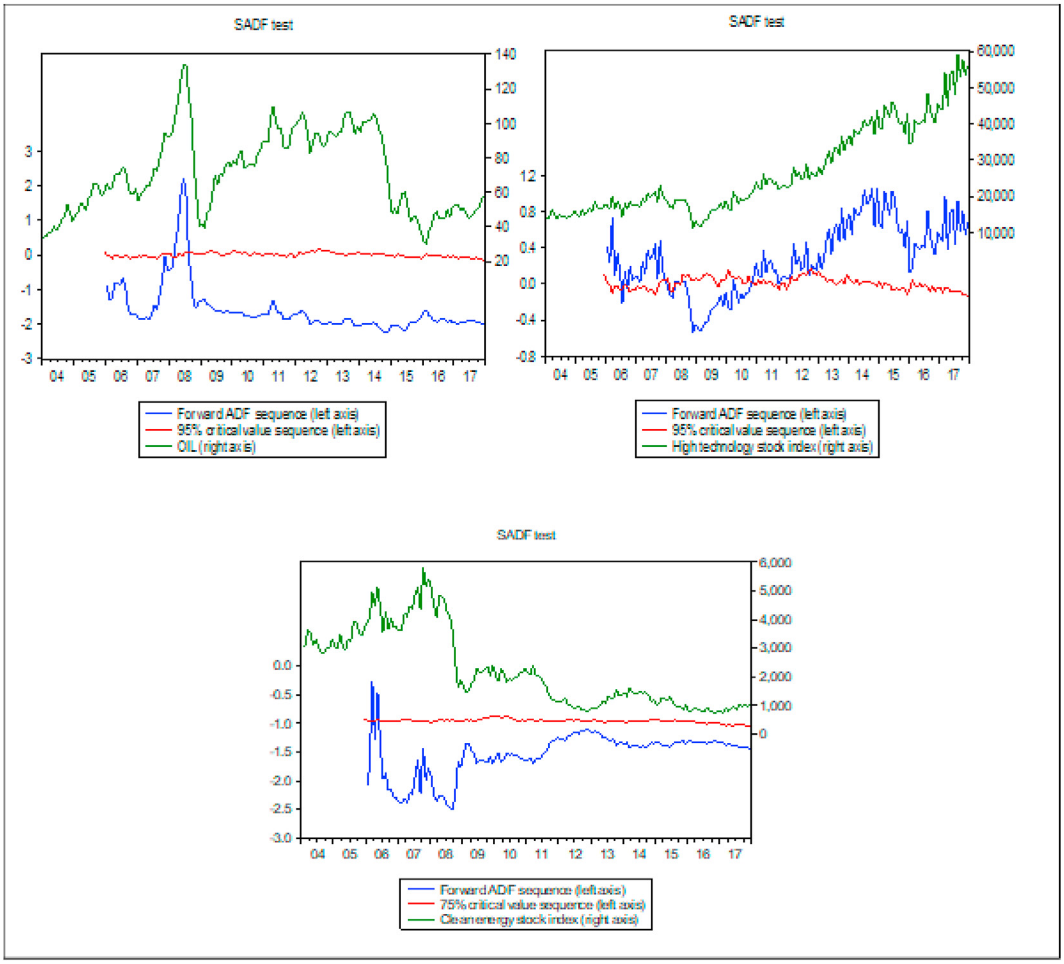

Fig. 2. The evidence of speculative bubbles for oil, technology stock, and clean energy stock price.

Table 2
Descriptive statistics and unit root tests.

Variable	Tests	Mean	Std. Dev.	Skewness	Kurtosis	J-B	Constant		Constant + Trend	
OIL		0.003172	0.089791	−0.900809	4.925420	48.38178	Level	Diff	Level	Diff
	ADF						−2.851[c]	−8.360[a]	−2.826	−8.378[a]
	DF-GLS						−1.633	−8.364[a]	−2.181	−8.417[a]
	ZA						−4.945[b]	−6.934[a]	−4.628	−7.103[a]
	F-ADF						−3.724[c]	−5.129[a]	−3.747	−5.050[a]
PSE		0.00835	0.09785	0.119366	2.92416	35.4366				
	ADF						−1.086	−16.424[a]	−2.664	−16.377[a]
	DF-GLS						−0.729	−16.455[a]	−1.824	−16.462[a]
	ZA						−0.503	−6.295[a]	−0.767	−6.391[a]
	F-ADF						−1.875	−7.427[a]	−2.514	−5.345[a]
ECO		−0.0065	0.116737	−0.09222	3.308171	22.89752				
	ADF						1.004	−2.839[c]	−1.202	−3.303[c]
	DF-GLS						1.633	−2.663[a]	−1.145	−2.692[c]
	ZA						−3.286	−8.139[a]	−4.097	−8.277[a]
	F-ADF						1.463	−7.340[a]	−2.929	−7.235[a]

Notes: Std. Dev. represents standard deviation. J-B: Jarque-Bera statistics. The ZA-ADF type critical values are −5.34 at 1%, −4.80 at 5%, and −4.58 at 10% (Break in level), and −5.57 at 1%, −5.08 at 5% and −4.82 at 10% (Break in level and trend). The F-ADF type critical values are −4.37 at 1%, −3.78 at 5% and −3.47 at 10% (Constant), and −4.87 at 1%, −4.31 at 5% and −4.02 at 10% (Constant + trend). The superscripts [a], [b], and [c] indicate significance level at 1, 5 and 10%, respectively. Oil: WTI crude oil prices, ECO: clean energy stock returns, PSE: high technology stock returns.

functions decrease constantly, implying that the sampling method yields uncorrelated samples.

Table 4 reports the estimates of the standard deviations, the posterior means, 95% credible intervals, Geweke convergence statistics, and the inefficiency factors, which is also known as relative numerical efficiency [30]. As for all the estimates, Geweke statistics do not allow us to reject the null hypothesis of the convergence of the posterior distribution for all the parameters, implying that convergence is achieved successfully with our time-varying model. The inefficiency factors are relatively low, and the 95% credible

Table 3
Pairwise correlation.

	ECO	PSE	OIL
ECO	1		
PSE	0.901171	1	
OIL	−0.03117	0.006912	1

Note: Oil: WTI crude oil prices, ECO: clean energy stock returns, PSE: high technology stock returns.

intervals include the estimates for the posterior means. Based on these diagnostic tests, we conclude that our time-varying model efficiently produces the posterior draws and does not suffer from imprecision in generating the impulse response functions.

4.1. Time-varying stochastic volatility

The posterior estimates of the stochastic volatility of the variables at study in the TVP-SVAR model are depicted in Fig. 3. The top chart plots the actual time series of each variables, while the bottom chart presents the dynamics of the estimated stochastic volatility of oil returns, clean energy, and high technology stock returns over the period $\sigma_{it}^2 = exp(h_{it})$ and based on the posterior mean and 95% confidence intervals. The graph shows that the stochastic volatility of clean returns remains constant but high over the experimental period. The time-varying volatility of oil price and high technology returns exhibits a relatively higher volatility for the period around 2004–2007. However, after 2008 the amplitude of the fluctuations remains relatively small and stably tended to be zero. One implication is that the stochastic volatility of oil price and high technology stock returns tend to co-move together and the most prominent point in the estimation of the stochastic volatility occurs before the global financial crisis. The higher volatility in oil prices and high technology stock returns can be accredited to the bubble observed in the bubble analysis of the series reported above. Another key observation is that high technology stock returns tend to be more volatile than oil and clean energy returns, which indicates that high technology returns carry the most risks. Overall, the non-constant structure of the posterior estimates valid the use of the TVP-SVAR model more suitable compared with the time-invariant VAR model.

4.2. Time-varying impulse response analysis

We conduct the impulse response analysis by ordering the variables from most to least exogenous variables, with oil prices being the first variable, followed by clean energy stock returns, then high technology stock returns. We present two types of time-varying impulse response functions over the sample period. Figure (4) shows impulse response functions at different point as in the traditional impulse responses from the VAR model. However, the impulse analysis of different points can consider several points to compute the static impulse responses based on TVP-SVAR model. Based on the findings from the explosive analysis, three points in time were selected, namely June 2006, March 2008, and July 2014. These periods perfectly match the estimated bubble dates detected in the series. For example, all the series detects an upward trending explosivity during these periods and includes the period whereby investments in high technology and renewable energy have experienced substantial increase (June 2006), the global financial crisis (March 2008), and the point when oil prices fluctuated sharply (July 2014). Figure (5) depicts the impulse response functions for three horizons: 6-, 12-, and 24-period ahead horizons. These impulse responses allow for the necessary statistical flexibility to assess the time-varying structure of the dynamics of the series at study.

Table 4
Preliminary tests.

Parameter	Estimates for the set (Oil, ECO, PSE)			Geweke	Inef.
	Post. Mean	Std. Dev.	95% CI		
$\Sigma_{\beta(1)}$	0.0023	0.0003	[0.0018–0.0028]	0.465	3.92
$\Sigma_{\beta(2)}$	0.0023	0.0003	[0.0018–0.0028]	0.919	6.66
$\Sigma_{\alpha(1)}$	0.0057	0.0017	[0.0034–0.0100]	0.797	39.95
$\Sigma_{\alpha(2)}$	0.0054	0.0016	[0.0547–0.2920]	0.669	26.30
$\Sigma_{\sigma(1)}$	0.1384	0.0615	[0.0034–0.0096]	0.263	31.55
$\Sigma_{\sigma(2)}$	0.0055	0.0017	[0.0034–0.0096]	0.518	46.45

Note: Post. Mean stands for posterior means, Std. Dev. denotes standard deviations, Geweke refers to the Geweke convergence statistics, 95% CI indicate the 95% confidence interval. Inef. shows the inefficiency factors. Oil: WTI crude oil prices, ECO: clean energy stock returns, PSE: high technology stock returns.

4.2.1. Impulse response for three different periods

Figure (4) shows that a unit positive shock to oil prices ($\varepsilon_{oil}\uparrow \rightarrow ECO$) has a positive influence on renewable energy stock returns and the response of clean energy returns is nearly the same on every specified date before the seventh period. This is followed by a slight upward trend and then finally reaches a stable state. The impulse response analysis demonstrates that after the global financial crisis, the long-term impact of oil prices has increased and continue to trend upward in contrast to the short-term impact. This finding suggests that the global financial crisis has caused a persistent positive influence of oil prices on clean energy returns. It could be argued that higher oil prices have a significant and persistent effect in boosting investment in renewable energy stock market due to the higher opportunity costs associated with oil-related projects. Our findings are in line with several previous studies [3,7,26,31].

A unit positive shock in oil price ($\varepsilon_{oil}\uparrow \rightarrow$ PSE) has a temporary small positive effect on high technology stock returns and then trend downward gradually in the long-term. This implies an asymmetric effect of oil price on high technology stocks with a significant time-varying after the third month. In the short-term a weak positive effect is observed, by contrast, a similar tendency of negative high technology response is observed for the three different periods in the long-term, although the response of high technology stocks during the GFC (March 2008) seems to be slightly more pronounced than those observed during the two other periods (June 2006 and July 2014), suggesting that the impulse responses significantly vary over different time periods. This finding indicates the prevalence of an overreaction of high technology stocks to oil price shocks mostly due to the effect of the global financial crisis of 2008. As reported by Refs. [32–34], oil shocks tend to exert significant severe impact on stock markets in the post global financial crisis period.

We find a weak negative response of oil prices from a positive shock to clean energy stock returns ($\varepsilon_{ECO}\uparrow \rightarrow$ OIL) around 0 and 3 months, while in the long-term, we observe an upward sloping trend in the response of oil prices to a positive shock to clean energy returns. The larger positive responses of oil prices stemming from positive shock in clean energy stock market suggests that the extensive use of clean energy may have a strong impact on oil demand in the long-run by driving up oil prices. This result reveals that contrary to expectations, investment in clean energy does not result into lower oil prices. The main implication is that the deployment of clean energy should be accompanied by additional policies such as imposing charge on emissions and emissions prices

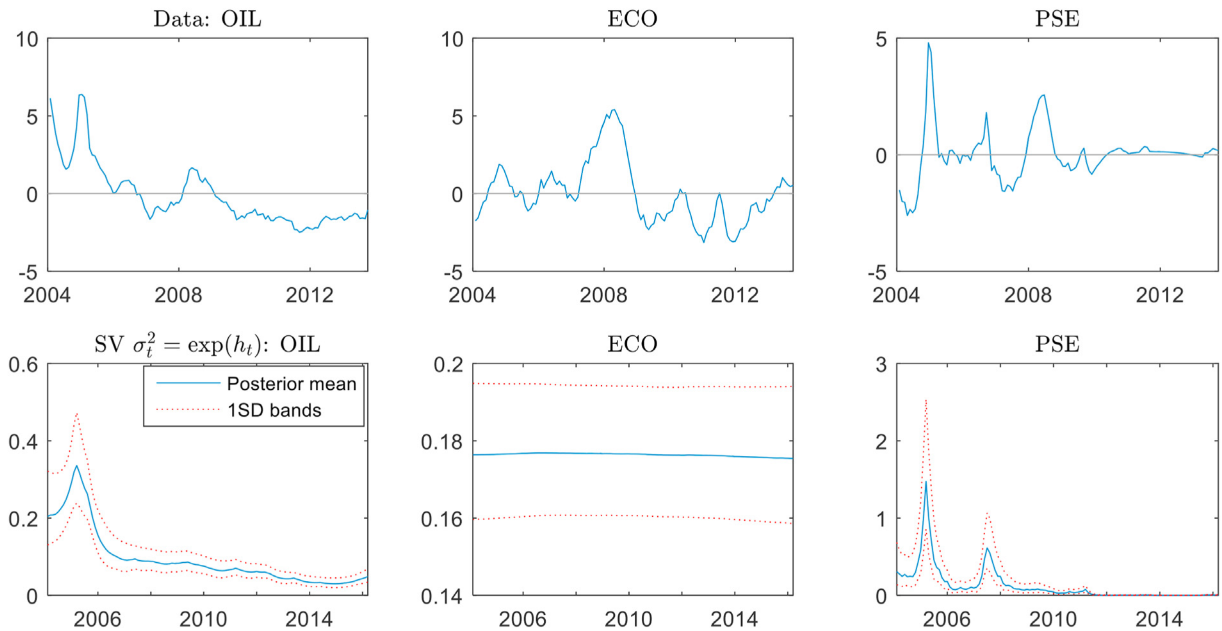

Fig. 3. Posterior estimation of the time varying stochastic volatilities of the structural shock. Oil: WTI crude oil prices, ECO: clean energy stock returns, PSE: high technology stock returns.

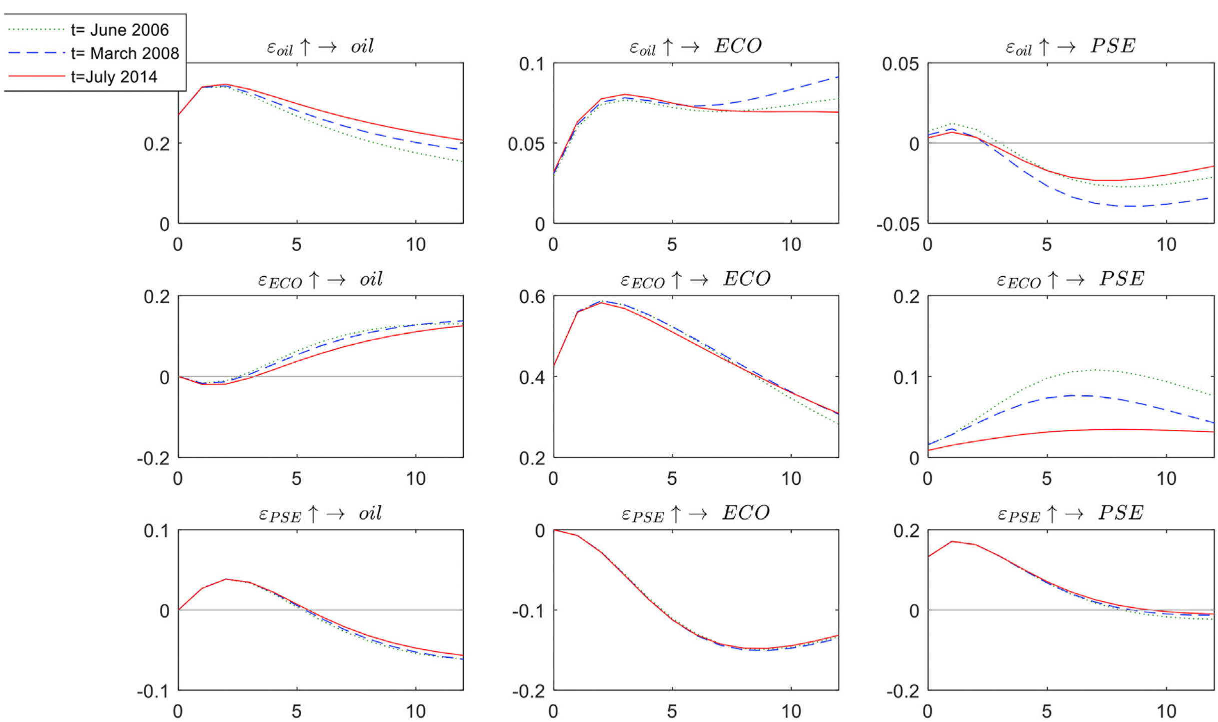

Fig. 4. Time-varying impulse response functions for June 2006, March 2008, and July 2014 for the TVP-SVAR model. Oil: WTI crude oil prices, ECO: clean energy stock returns, PSE: high technology stock returns.

to be more effective in cutting oil demand and hence, oil prices [35]. The responses of oil prices are quite similar during the three specified periods.

The responses of high technology returns to clean energy returns shock ($\varepsilon_{ECO}\uparrow \rightarrow$ PSE) is positive and vary in different ways depending on the three representative dates. A positive clean energy stock return shock in July 2014, has a weakly significant effect that decreases sharply after 10 months and then moves to zero. A shock occurring in March 2008 (global financial crisis) has a positive and significant effect throughout the sample period, although the response of high technology returns decreases sharply for a period after 8 months. The more pronounced response of high technology returns is observed for a unit positive shock on clean energy returns after the increasing wave of investments in high

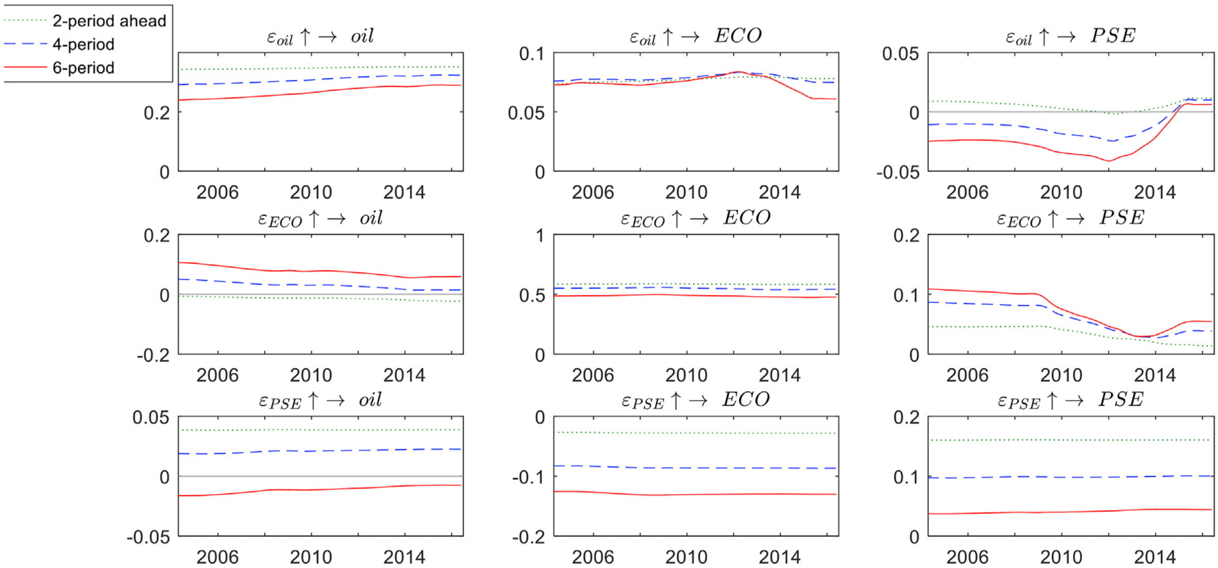

Fig. 5. Impulse response analysis of oil price, ECO, and PSE at different horizons.

technology stocks in June 2006, as high technology raises by 0.1 in response to a one standard deviation shock to ECO. A key observation is that the positive responses of high technology returns to a unit clean energy shock are somewhat less persistent with little volatility. This finding is mostly due to the key role of high technology in the process of clean energy production in such a way that there is a strong correlation among them. One major implication is that investors should be cautious about such a linkage between returns in their portfolio diversification strategies.

A positive shock in high technology stock market ($\varepsilon_{PSE}\uparrow\ \rightarrow$ OIL) lead to a positive response of oil prices until during the first 5 months, and after that there is a negative effect of high technology stock returns on oil prices. Intuitively, the stance of positive response lends evidence on the small degree of cointegration between (oil and high-tech stock markets) in the short-run. Because the increase in high technology investments would not result immediately into a substitution effect away from oil-based energy towards alternative energy technology sources. Thus, one implication is that both high-tech stock returns and oil prices increase in the short-run. However, it is only in the long-run that investment in high technology would drive down oil prices through for instance, the deployment of energy research, development, and demonstration technology, which makes high-tech energy sources comparatively more competitive. More importantly, the impulse responses are nearly the same over the different three periods.

The impulse response functions of clean energy returns to high technology return shocks ($\varepsilon_{PSE}\uparrow\rightarrow ECO$) show a similar tendency throughout the three different dates in the sample. The impulse response of clean energy returns to high technology return shocks shows a downward sloping trend until around 10 months and then remains constant. This finding implies that clean energy returns do not possess hedging characteristics against shocks in high technology stock markets.

4.2.2. Impulse response functions for the three periods ahead

Fig. 5 plots the impulse responses for selected horizons 2, 4 and 6 periods ahead after structural shocks. One key observation is that the impulse response patterns are quite different across horizons. Focusing on the response of clean energy returns to oil price shocks ($\varepsilon_{OIL}\uparrow\rightarrow ECO$), we observe that the responses are nearly the same across horizons from the beginning of the sample period to the late 2014. For the longer horizons, however, the response pattern of clean energy returns is somewhat different from those of the 2 and 4 months ahead. More importantly, the impulse responses of clean energy returns to oil price shocks remain positive throughout different horizons.

For the response of high technology to oil price shocks ($\varepsilon_{OIL}\uparrow\rightarrow PSE$), the impulse responses vary in different ways based on the different periods ahead. The 2-month horizon response is positive and weakly significant until around 2012, while the impulse response associated with 4 and 6 months decrease monotonically over time during the same period. However, the most dramatic effect is observed for the longer period ahead (6-period). However, the impulse responses associated with all the periods ahead are somewhat similar and close to zero after 2015. As the result shows, the temporary positive response of high technology to oil price shocks is only observed during shorter horizons. This is consistent with [4], who estimated a strong negative influence of oil prices on high technology. This is because higher oil prices drive down cash flows of technology oriented businesses [6].

We find a relatively positive response of oil price to clean energy stocks ($\varepsilon_{ECO}\uparrow\rightarrow$ OIL). The response of oil price tends to be statistically insignificant throughout the sample period for the 2-months responses. The 4-months responses display a downward tendency over the sample period, while the 6-months responses tend to be more or less constant throughout our sample. The impulse response analysis indicates that the effects of clean energy stock are positive and decline gradually in generation. This finding can be explained by the speculation behavior of investors. Indeed, investors display more pessimistic behaviors towards oil related stocks during episodes of higher returns in renewable energy stocks, which in turn might translate in gradual drop in oil prices in the long-term.

The impulse response analysis indicates that high technology stocks respond positively to a one standard deviation in clean energy stocks ($\varepsilon_{ECO}\uparrow\rightarrow$ PSE). The response is relatively steady until around 2010, with the strength of impulse response gradually weakening as the period passes. However, a sharp decrease in the response of high technology is observed during 2014. This is because the sharp decline in oil prices during 2014 has led to a contagion effect in clean and high technology stock markets in the post oil-price shock period, compared to other previous periods of stability. Thus, it could be argued that the oil price shock of 2014 has led to a more pronounced impact of the response of high technology to clean energy shocks and the response does not change significantly over different horizons after the oil price crash.

The impulse response of oil price to a positive shock from high technology returns ($\varepsilon_{PSE}\uparrow \rightarrow$ OIL) vary significantly over horizons. We observe a declining response of oil price for the 6-period horizons to a positive shock in high technology returns. By contrast, for the 4, and 6 months horizons the response of oil price is positive and tends to be more stable. However, comparing the response values across horizons, we notice that a higher response of oil prices is reported for the shorter horizon, corresponding to 2-month horizons.

Another important finding is that the responses of clean energy returns to high technology shocks ($\varepsilon_{PSE}\uparrow \rightarrow ECO$) do not change over time. The main implication is that the stock return volatilities of high technology returns have no effect on investors' expectations of clean energy returns. They believe that the dynamic of clean energy returns is difficult to change over an extended period, consequently, the clean energy returns expectations of investors remain stable. We observe that the average responses value of oil prices to high technology return shocks are higher than those of the clean energy returns to high technology returns for the entire sample period. These findings imply that shocks to high technology have a larger impact on oil prices than on the stock of clean energy companies.

4.2.3. Robustness tests

Against the backdrop that the VAR model is sensitive to alternative variables, in this section, we re-estimate our benchmark model by using Brent crude oil price instead of WTI price and check how our impulse response results change when Brent crude oil price is used in the TVP-SVAR model. By comparing the impulse response graphs, it is found that the dynamic trends are similar to our baseline specification (Figs. 6 and 7 quantitatively match those of Figs. 4 and 5), indicating that the TVP-SVAR model is robust to different measures of oil price.

5. Discussions and result implications

In this study, the focus is to examine the co-movements between oil prices and the stock prices of clean energy and technology companies by accounting for nonlinearity, structural shift, and time-varying dynamics in the behavior of the series. To do so, we first employ the GSADF test and the BDS test to inspect how the underlying series behave over times, and later, we examine the co-movements between variables by using the TVP-SVAR model to account for potential explosive structure and nonlinear behavior in the temporal dynamic of the series. While previous research studying the relationship between oil prices, clean energy and high technology stock indexes implicitly assume linearity or time-invariant dependence among variables, our study provides a more realistic exploration by identifying key periods of stock returns exuberance and potential bubbles in the series and study the dynamic interaction among variables in a TVP-SVAR setup at different bubble periods.

Firstly, the empirical results show that the time varying behavior of the dependence among clean energy, high technology stocks and oil future prices is due to major bubbles in the series. All the series exhibit an upward trending explosivity during three periods, including the period whereby investments in high technology and renewable energy have experienced substantial increase (June 2006), the global financial crisis (March 2008), and the point when oil prices fluctuated sharply (July 2014). Similar bubble episodes have been reported by Zhao et al. (2021). Using the GSADF approach, the authors identified two bubble episodes in crude oil prices and Chinese stock market, namely the 2007–2008 global financial crisis and 2014–2015 oil excess capacity bubbles. Identifying a bubble for these periods supports the characterization of the overall sample period as one of the most unstable for clean energy and high technology stock markets. Following Ajmi et al. (2021), we consider these different benchmarks of oil prices, clean energy and high technology stock markets to investigate whether their bubble occurrence influence the interaction among the series.

Secondly, the GFC exerts a significant impact on the impulse responses of the series and most relationships between clean energy, high technology stocks and oil prices vary substantially over time. For instance, the responses of clean energy and high technology stocks to the oil price shock change over time and high technology tends to be more susceptible to oil price shocks. This finding implies that renewable energy companies seem to be more immune to oil price shocks than those in high technology industries. One key implication is that oil prices remain effective in boosting clean energy investments as the impulse responses of clean energy returns to oil price shocks remain positive throughout different horizons (2-4-6 periods ahead). The findings of this work confirm a whole list of works dealing with the positive relationship between oil price shocks and clean energy stocks, the most recent of which are He et al. (2021), Shao and Zhang (2020), and Uddin et al. (2019). What seems most interesting in our study is that, the global financial crisis has played a key role in the co-movement between oil prices and clean energy stocks as they tend to crush and boom together, which is in accordance with Uddin et al. (2019). Additionally, we report that, it would be useful for investors in high technology markets to immune against oil shocks, particularly in the medium and long-term (4 and 6 months ahead) after the occurrence of oil price shocks. This is not expected as previous studies have demonstrated that the risk transfer from oil to technology stocks is not significant at all time horizons (see e.g. Ref. [7]; Maghyereh et al., 2019).

Thirdly, we find that oil prices and high technology stocks respond positively and significantly to shocks in clean energy stock index in the long-term. Thus, contrary to expectations, investment in clean energy does not result into lower oil prices. The main implication is that the deployment of clean energy should be accompanied by additional policies such as imposing charge on emissions and emissions prices to be more effective in cutting oil demand and hence, oil prices in the long-run. This finding is in accordance with previous studies stressing the need to balance between supply- and demand-side factors in order to reduce the greater dependence on oil consumption [35]; Betancourt-Torcat et al., 2012; Zhao et al., 2018). In addition, the long-run interaction between oil and clean energy markets is also consistent with (Niu, 2021), who found that the long-term correlation between pairwise oil and clean energy markets is higher than the short-term on average. However, the positive response of high-tech stocks indicates that the success of new energy companies likely dependent on the development of specific technology. This finding is consistent with (Niu, 2021; [8]. Interestingly, we observe that the response values of oil prices to clean energy shock are quite similar to those of the high technology to clean energy shocks, especially in the long-run (6-month horizons). This cause an important dilemma for investors when they decide to invest in oil future and high technology stocks.

6. Conclusion and policy recommendations

We have studied the dynamic interaction between oil prices and

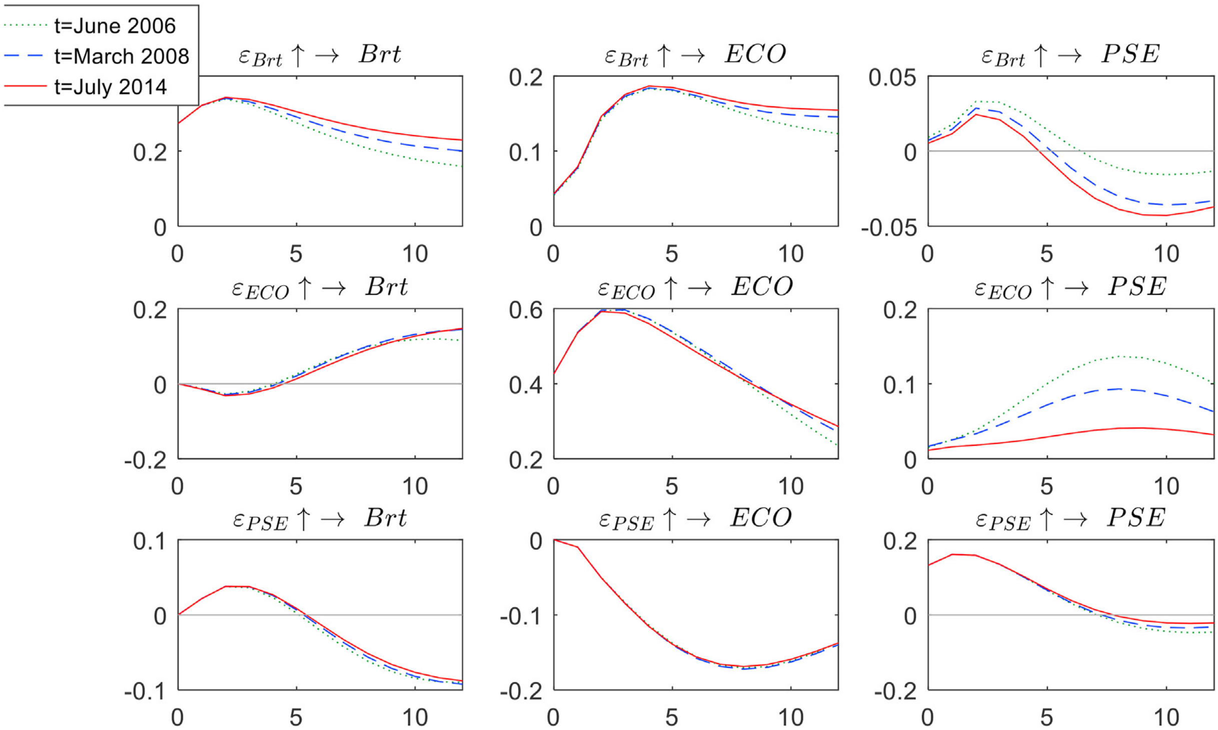

Fig. 6. Impulse response results of Brent oil prices (Brt), clean energy stock returns (ECO) and high-technology stock returns (PSE) in three different dates of sample.

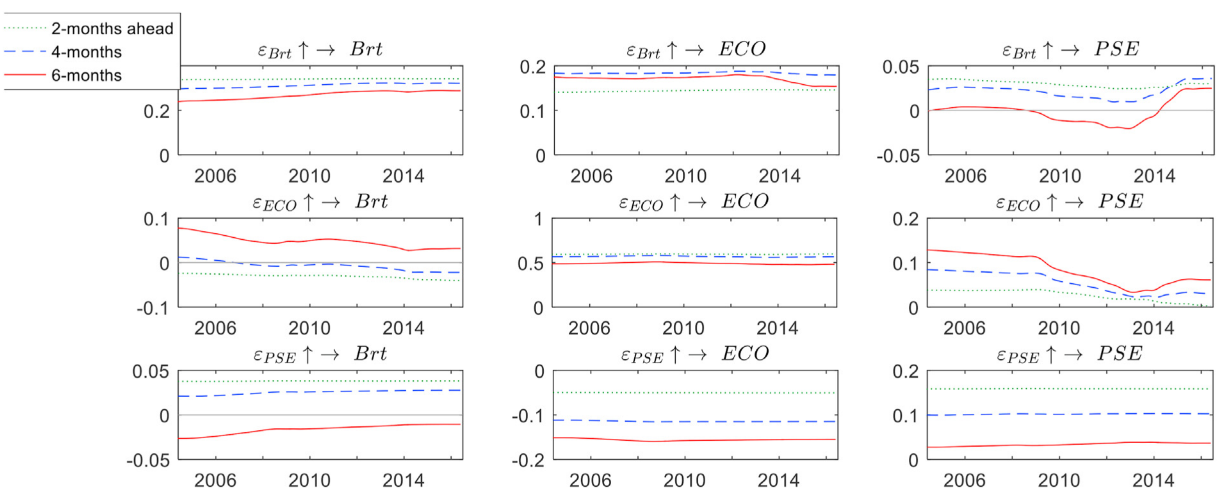

Fig. 7. Impulse response of Brent oil prices (Brt), clean energy stock returns (ECO) and high-technology stock returns (PSE) at different time horizons (2, 4, and 6 months ahead).

clean energy and high-tech asset returns in a TVP-SVAR setup. This method addresses nonlinearity and structural shifts in the relationship between variables and perfectly controls for exuberant periods and explosive behavior in the data generating process as well as changing in the impulse responses across time horizons. The use of the TVP-SVAR framework is justified by both nonlinear structure and explosive bubbles in the evolution of the series. We account for these features by conducting the nonlinearity tests developed by Ref. [17] and explosive break tests through the method proposed by Ref. [18].

Simulation results show that the global financial crisis exerts a significant impact on the impulse responses of the series and most relationships between clean energy, high technology stocks and oil prices vary substantially over time. We find that oil disruption shock resulting in higher oil prices is effective in boosting clean energy investments, mainly due to substitution motives between fossil fuels and clean energy. Contrary to expectations, we demonstrate that investment in clean energy does not result into lower oil prices. One may argue that the deployment of clean energy should be accompanied by additional policies such as imposing charge on emissions and emissions prices to be more effective in cutting oil demand and hence, oil prices in the long-run. The asymmetric responses of oil prices to high technology shocks indicate that investors in oil future markets should adopt a time-varying hedging strategies against shocks in high-tech stock markets.

6.1. Policy recommendation

Our results have important implications for investors, and policymakers. Given that we have verified the existence of time-varying nexus between oil, clean energy, and high technology markets, we strongly encourage investors, as well as portfolio managers, to decouple the time-varying interactions between oil prices and high-tech and clean energy stock indexes so that they can maximize their returns by allocating assets over different periods. As a result, investors behavior can vary under different horizons. As they are heterogeneous in their investment horizons, investors in high technology markets should immune against oil shocks, particularly in the medium and long-term. The bubble episodes evidenced in our study indicate that policymakers should improve the regulation of oil future markets, high-tech and clean energy stock markets to avoid the damaging effects of the bubbles to the overall economy. Additionally, the positive relationship between oil prices and clean energy suggests that policymakers should avoid actions that mitigate higher oil price instead, they should take advantage of episodes of higher oil prices as they create incentives to invest in clean energy stock markets. As a result, the scaling up policy of the clean energy technology investment should be further increased globally during episodes of higher oil prices. Although the development of the CCUS technology is currently limited to Europe and the United States, climate finance policies should be adequately promoted especially among the emerging economies.

However, future study could implement the same approach by considering the specific indexes of the different renewable and clean energy mix. In addition, future study could utilize the variance decomposition technique to further provide a robustness support and such that highlight the variance attribution of the variable.

Credit author statement

Yacouba Kassouri: Data curation; Writing – original draft; Conceptualization; Formal analysis; Investigation and Methodology. Andrew Adewale ALOLA: Writing – review & editing; Visualization; and Corresponding. Kacou Kacou Yves Thierry: Supervision and Validation.

Declaration of competing interest

The authors declare that they have no known competing financial interests or personal relationships that could have appeared to influence the work reported in this paper.

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Appendix A

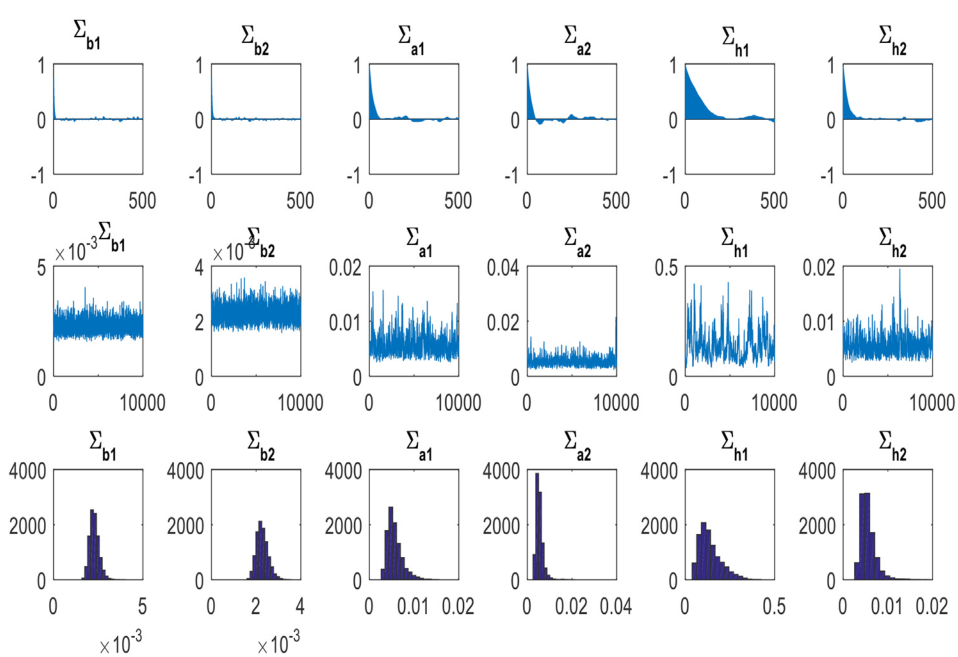

Fig. A.1. Estimated results of the sample autocorrelation (top chart), sample paths (middle chart), and posterior densities (bottom chart).

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