Resources Policy 72 (2021) 102083

Contents lists available at ScienceDirect

Resources Policy

journal homepage: http://www.elsevier.com/locate/resourpol

Counterfactual shock in energy commodities affects stock market dynamics: Evidence from the United States

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ARTICLE INFO

Keywords:
Dynamic simulated ARDL
DYNARDL
Energy commodities
Stock market dynamics
Energy prices

ABSTRACT

Volatilities in the stock market are due to fluctuations in essential energy commodities. This in effect underpins the impact of short- and long-run prices on producers, consumers, portfolio managers, and policymakers. To understand the past, present, and future dynamics of energy commodities and stock market uncertainty — this paper investigated the nexus between real stock index in the US. We investigated energy commodities namely oil price, coal price, and natural gas price employing over decadal monthly data from 1991:01 to 2019:12. The study applied autoregressive distributed lag (ARDL) and dynamic simulations of ARDL (DYNARDL) techniques to investigate long-term shocks in oil price, coal price, natural gas price, short-term interest rate, and industrial production index. The study found negative long-run relationship between real oil price, real coal price, real natural gas price, short-term interest rate, and real stock index, with only industrial production index reporting a positive relationship with real stock index in both ARDL and dynamic simulated ARDL models. While we found positive relationship between energy commodities and real stock index in the short run, negative relationship was reported between short-term interest rate, industrial production index, and real stock index. Incorporating real Western Texas Intermediate oil in S&P500 stock price index function corrects historical fluctuations by 64% compared to 54% speed of adjustment with real brent oil. The dynamic ARDL simulation further provides key insight into how energy commodity prices and economic activity shocks are transmitted to stock market prices in the U.S.

1. Introduction

Energy commodities are one of the vital natural resources used by countries as input in many economic sectors including industry, transportation, and among others—that ensures economic stability and enhances national security. The major trading energy commodities commonly used across countries include oil, natural gas, and coal. The oil demand rose steadily in 2018 with its major consumption in the United States alongside China and India. The US is currently the leading gross oil exporter after overtaking Saudi Arabia in mid-2020 and remains the leading importer of heavy crude oil (IEA, 2020). Natural gas consumption increased by 4.6%, accounting for nearly half of the global energy consumption. About 80% (est. 2010) of the growth is concentrated in the US, China, and the Middle East (IEA, 2020). The global demand for coal energy rose consistently for two years since 2018. In Asia, coal-driven electricity supply remains critical to meet the growing demand in China, Indonesia, India, south, and east Asia (IEA, 2020). Because coal and natural gas are the major sources of electricity and heating, increment in the price of energy commodities is expected to affect household cash flows. In contrast, oil is a fundamental input for industrial production, thus, strongly affects inflation rates. The impact of economic activities on the stock market dynamics, particularly the interest rate and industrial production index were investigated in this study. Interest rate is one of the important monetary policies in the economy—directly increasing the cost of capital, consumer purchasing power, and savings.

The global pandemic has exposed how fragile the world economy and commodity react to external shocks (Yakubu et al., 2021). For instance, the COVID-19 oil demand shock triggered an estimated 10% decline in demand—leading to more than 60% fall in price from January to April 2020. To arrest the shock, OPEC members agreed to cut oil production by an estimated 9.7 million b/d in April 2020 (WorldBank, 2020). The oil price fluctuation in the 1970s attracted much interest from academia, financial investors, and policymakers due to its role as important factor production of various economic sectors for both oil-importing and exporting countries. Early pioneers examined the

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https://doi.org/10.1016/j.resourpol.2021.102083
Received 8 January 2021; Received in revised form 22 March 2021; Accepted 22 March 2021
Available online 31 March 2021
0301-4207/

relationship between oil price and economic activities—by demonstrating the significant impact of oil price on macro-economic activities and partly responsible for post-WWII U.S. recession from 1973 to 1975 (Hamilton, 1983). Since then, several studies have detailed similar findings of oil price effects on economic variables (Hamilton, 2008; Hamilton and Herrera, 2004; Huang et al., 1996; Jones et al., 2004; Nakov and Pescatori, 2010; Segal, 2011). Several other studies investigated the link between oil price shock and financial stock market in the US—showing financial market performance reacts negatively to oil price shocks (Jones and Kaul, 1996; Park and Ratti, 2008; Sadorsky, 1999). The findings from existing studies indicate significant positive correlation between crude oil price and stock-implied volatility return index, particularly during the financial crisis (Liu et al., 2020). Similarly, real oil price shock, reflecting oil supply or demand shock has different effect on oil price and macroeconomic factors (Kilian, 2009). In contrast, insignificant relationship between U.S stock return and daily price of oil future is reported (Huang et al., 1996), whereas others found non-linear significant relationship between oil price future and real stock return (Ciner, 2001). The great oil price shock does not influence the U.S. stock market index (Alsalman and Herrera, 2015; Blendon et al., 2008) whereas the impact of oil price shock is not limited to stock return but extend to bond market on the global financial market (Demirer et al., 2020). The dynamic relationship between 17 stock mmarketsand brent oil prices revealed the impact of stock market development on crude oil market grows overtime (Gomez-Gonzalez et al., 2020). Empirical evidence from the Markov-copula model indicates that oil price dynamics significantly affect G-7 stock market returns in volatility regime than during tranquility regime (Tiwari et al., 2020). Thus, the substantial co-movement between crude oil and stock market price volatility is further reported in Asia (Sarwar et al., 2020).

Most studies employed vector autoregression (VAR) to examine the relationship between oil price shock and the stock market (Bastianin et al., 2016; Huang et al., 1996; Sadorsky, 1999). The findings from existing studies show a shock in the monthly price of real oil price has significant impact on the monthly real price of S&P 500. On the contrary, daily oil future return has insignificant impact on daily U.S financial benchmark indices like S&P 500 (Huang et al., 1996). The unrestricted multivariate VAR model was used to investigate the dynamic connection between oil price shock and stock market price. Stock market prices are significantly affected by shocks in monthly oil prices (Park and Ratti, 2008). The major challenges associated with applying the VAR approach is over-parameterization and in-sample perspective identification. These challenges can be resolved by excluding some variables in the model to restrict the endogenous variable, however, such estimation procedure is argued to often have little theoretical justification (Cooley and LeRoy, 1985). Thus, this technique of variable exclusion leads to omitted-variable and estimation bias that affect statistical inferences. In this scenario, this study adopts the dynamic simulated ARDL and standard ARDL techniques useful in assessing dynamic processes. The adoption of novel estimation techniques that control for omitted-variable bias, and endogeneity is essential to improve the model specification, robustness and consistent estimates—leading to unbiased statistical inferences.

Recent empirical studies focus mainly on the impact of oil price changes on stock market dynamics, excluding other primary energy commodities affected by price fluctuations in the US. The US energy utilization reported in 2019 shows an energy portfolio comprising 37% petroleum, 32% natural gas and 11% coal. Domestic energy production in the U.S grew by 5.7% in 2019 with fossil fuel accounting for 80% of production. Natural gas is the leading domestic energy production in the U.S as of 2019, accounting for 35%, whereas petroleum or crude oil and coal account for 31% and 14%, respectively (EIA, 2020). Natural gas is the cleanest source of burning fuels with low greenhouse gas emissions—–accounting for 23% growth in global energy demand. The global coal trade value increased by 148.1% since 2000, however, 92% of coal is consumed in the US through electricity generation (EIA, 2020). The fluctuations in crude oil prices have largely impacted changes in refined oil by-products, but do not entirely explain the disturbances in the energy price. These studies show that though the price series between oil and natural gas are cointegrated, the relationship shifts drastically overtime (Brigida, 2014; Ramberg and Parsons, 2012). Therefore, using alternative energy fuel prices such as natural gas and coal are useful in assessing the movements in the stock market. For example, crude oil prices rose by 83% and 12% in the intermediate energy product during the Gulf War in 1990. Hence, different research or policy questions may require different approaches for energy price shocks (Kilian, 2008).

Americans of middle and lower-income levels cited gasoline and gas prices as one of the main economic issues facing household consumption and livelihoods (Blendon et al., 2008). The increase in energy commodities including oil and natural gas prices will increase the production cost of companies that utilize oil and gas—could influence cashflows and indirect profits—thereby increasing the stock price and pushing the stock market to bullish (Degiannakis et al., 2018). The relationship between energy market and stock plays an important role in investor's portfolio strategy and performance (Gatfaoui, 2019; Rehman et al., 2019). For instance, the impact of energy market price on developed and emerging markets differ with production structure (Balcilar et al., 2019). The recent unprecedented increase in the production of crude oil and natural gas in the US calls for further evidence in the linkage between energy price and stock movement—–while adopting additional energy commodities—–to shed light on the dynamic new challenges faced by producers, consumers, portfolio managers, and policymakers. Contrary to previous attempts in extant literature limited in both scope and methodology, we for the first time employs novel dynamic stochastic simulations of the popular autoregressive distributed lag model that accounts for real-time fluctuations and dynamics from a multivariate normal distribution draws with stochastic uncertainty used for predictions. In this regard, over-parametrization, and counterfactual shocks in the prediction process can be controlled. This procedure is essential to derive new perspectives from robust and consistent technique that examines the impact of counterfactual shock of energy commodities on stock market while accounting for real-time price volatilities.

This study empirically examines the relationship between shocks in energy commodities and economic productivity. To do this, we employ the ARDL and dynamic simulated ARDL techniques to investigate the short-run and long-run relationships. Contrary to existing studies (Alsalman and Herrera, 2015; Demirer et al., 2020; Huang et al., 1996; Jones and Kaul, 1996; Park and Ratti, 2008; Sadorsky, 1999; Sarwar et al., 2020) based on traditional models, we use the novel dynamic ARDL approach to estimate the effects of monthly counterfactual shocks in energy commodity price and economic dynamics on the US stock market. Second, we use both standard ARDL (Pesaran et al., 2001) and dynamic simulated ARDL (Jordan and Philips, 2018) models to estimate the short-run and long-run relationship between exogenous variables including oil price, coal price, natural gas price, short-term interest rate, and industrial production index. In contrast, we adopt stock market price as endogenous variable. The dynamic ARDL model used herein examines the dynamic interaction between the impulse-response of energy commodities price and other economic variables in short- and long-run. Our empirical findings corroborate existing findings that oil price shock stimulates statistically significant impact on the US stock index. Our findings on short- and long-run relationships, and effects of counterfactual shock in energy commodities on the US stock market could be informative to financial institutions, and investors to make investment strategies in terms of portfolio diversification and hedging against potential energy market shocks.

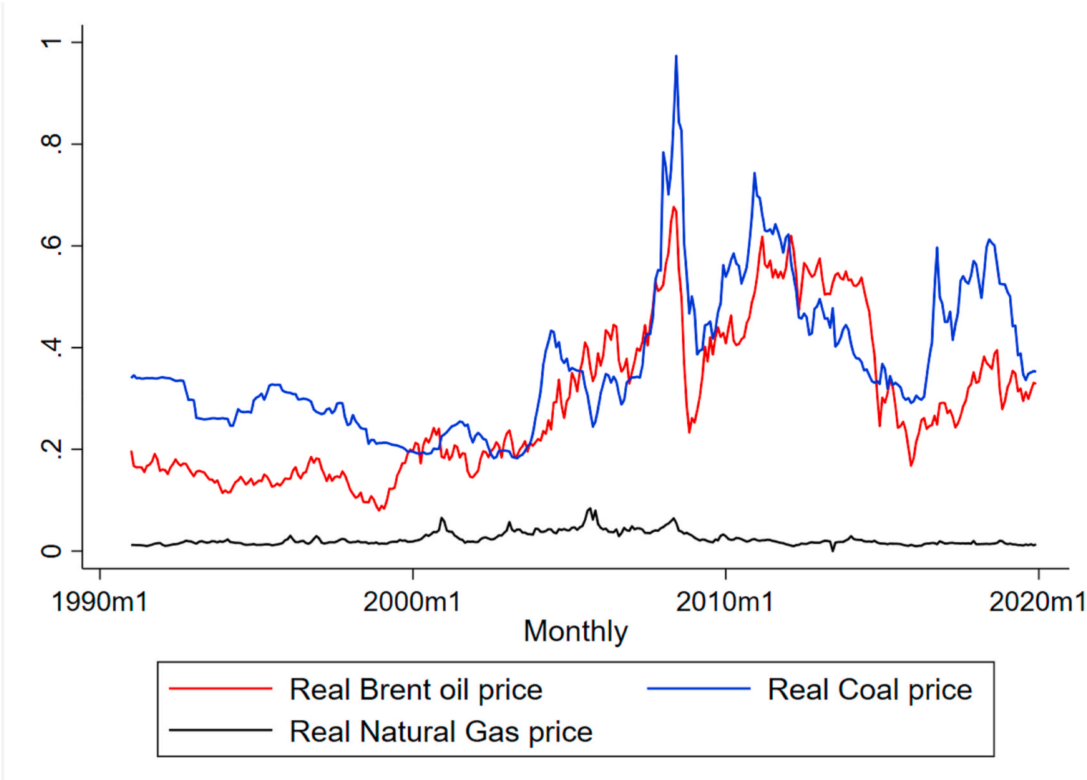


Fig. 1. The trend of real brent oil price, real coal price, and real natural gas price.

2. Materials & method

2.1. Data

This study examines the effect of energy commodities price shock on the US real stock market return with monthly data spanning 1991:01—2019:12. We employed the ARDL and dynamic ARDL stochastic simulated models to capture the complexities of the dynamic relationships between the sampled variables in the study. We consider energy commodities such as UK Brent oil, West Texas Intermediate (WTI) oil, coal, US natural gas, and other variables including short-term interest rates, industrial production index, consumer price index, and producer price index. The effect of real energy commodities on real stock price nexus may be influenced by other variables included in this study. The industrial production index is used as a proxy indicator for cashflow analysis of energy commodities shock and stock price—suggested in the existing studies on oil price shock and stock prices (Jones and Kaul, 1996; Park and Ratti, 2008).

The industrial production index, consumer price index, producer price index, and three months treasury-bill rate data were retrieved from the U.S. Federal Reserve Economic Data (FRED, 2020). The nominal oil price is taken as the UK Brent oil index in the U.S. dollar, U.S. natural gas price, and Australian coal market price was also retrieved from International Monetary Funds (IMF) and the S&P500 stock price index from Yahoo Finance (IMF, 2020; YahooFinance, 2020).

Following the data processing procedure presented in Park and Ratti (2008), we calculated real oil price as a ratio of nominal oil price to the US producer price index of all commodities. This was then adopted to calculate the real oil price, real natural gas price, and real coal price variables used in this study. Evidence from Fig. 1 shows real oil and real coal prices exhibit a volatile pattern of price behavior by increasing frequently in the first-half of the sample but depicts market volatility in the second half of the same period. However, real natural gas price shows quite stable trend throughout the sample period.

The real stock return is calculated as the difference between continuous compounding return of S&P500 index and log-difference in the US consumer price index as proxy for inflation—as suggested by Ref. (Park and Ratti, 2008). Three months U.S. treasury-bill rate is taken as proxy for short-term interest rate. The notations employed in this paper are expressed as:

ROIL: log first-difference of real brent oil price
RWTI: log first-difference of real WTI oil price
RCOAL: log first-difference of real coal price
RNGAS: log first-difference of real natural gas price
SHTI: log first-difference of three months treasury bill rate
IPI: log first-difference of industrial production index
RSTOCK: log of real S&P500 stock price index

2.2. Model estimation

The study employed the ARDL cointegration approach proposed by Pesaran et al. (2001). The underlining variables for cointegration can be a combination of *I(0)* or *I(1)* or without pre-specification of the variables that are either *I(0)* or *I(1)*. However, it cannot be applied to *I(2)* variables. The ARDL is a single dynamic model equation and error correction model (ECM) that reparametrize and examines short-run and long-run relationships of the variables by distinguishing between endogenous and exogenous variables. Besides, it absorbs adequate number of lags to capture the data generating process in general-to-specific model (Laurenceson and Chai, 2003; Pesaran et al., 2001). Pesaran and Shin (1999), provide evidence that ECM integrates short-run adjustment with long-run equilibrium without losing long-run information in that process. The ARDL model employed in this study captured the cointegration estimates of the long-run equilibrium relationship between RSTOCK and exogenous variables (ROIL, RCOAL, RNGAS, SHTI, and IPI). The ARDL model can be expressed as:

Table 1
Descriptive statistics

Statistics	RSTOCK	ROIL	RCOAL	RNGAS	SHTI	IPI
Mean	2.7150	0.2904	0.3682	0.0238	2.5386	92.1945
Median	2.7149	0.2468	0.3364	0.0188	2.2200	95.3375
Maximum	2.7346	0.6767	0.9735	0.0841	6.2200	110.5516
Minimum	2.7035	0.0798	0.1825	0.0094	0.0100	62.1190
Std Dev	0.0027	0.1471	0.1414	0.0130	2.0639	13.2434
Variance	0.0000	0.0216	0.0200	0.0002	4.2596	175.3867
Skewness	1.3211	0.6469	1.0973	1.6131	0.1657	-0.8622
Kustosis	12.4158	2.2535	4.1748	5.9124	1.4982	2.6310
Jarque-Bera	0.0000	0.0000	0.0000	0.0000	0.0000	0.0000
Observation	348	348	348		348	348

Table 2
Unit root tests.

DATA SERIES	Dickey-Fuller Test		Philip-Perron	
	Level	1st Diff	Level	1st Diff
RSTOCK	-11.078***		-10.958***	
ROIL	-1.637	-16.325***	-1.920	-16.275***
RWTI	-1.556	-14.914***	-1.809	-14.820***
RCOAL	-2.044	-14.780***	-2.470	-15.011***
RNGAS	-3.355	-17.814***	-3.201	-17.824***
SHTI	-1.723	-16.223***	-1.859	-16.077***
IPI	-2.348	-14.987***	-1.920	-15.999***

Note: *** indicates the rejection of the null hypothesis of unit root test at 1% significant level.

$$\begin{aligned}\Delta RSTOCK = \beta o + \sum\nolimits_{i=1}^{p} \delta_i \Delta RSTOCK_{t-i} + \sum\nolimits_{i=1}^{q} \delta_{2i} \Delta ROIL_{t-i} \\ + \sum\nolimits_{i=1}^{q} \delta_{3i} \Delta RCOAL_{t-i} + \sum\nolimits_{i=1}^{q} \delta_{4i} \Delta RNGAS_{t-i} + \sum\nolimits_{i=1}^{q} \delta_{5i} \Delta SHTI_{t-i} \\ + \sum\nolimits_{i=1}^{q} \delta_{6i} \Delta IPI_{t-i} + \alpha_1 RSTOCK_{t-1} + \alpha_2 ROIL_{t-1} + \alpha_3 RCOAL_{t-1} \\ + \alpha_4 RNGAS_{t-1} + \alpha_5 SHTI_{t-1} + \alpha_6 IPI_{t-1} + \varepsilon_t \end{aligned} \tag{1}$$

Where β represents the intercept, p is the lag order of endogenous variable, q is the lag of order of exogeneous variables, ε_t represents the white noise, Δ is the difference in the regressor. To test for long-run equilibrium relationship in this study, the null hypothesis of no cointegration between RSTOCK, ROIL, RCOAL, RNGAS, SHTI, and IPI is H_o: $\alpha_1 = \alpha_2 = \alpha_3 = \alpha_4 = \alpha_5 = \alpha_6 = 0$ against the alternative hypothesis H_1: $\alpha_1 = \alpha_2 \neq \alpha_3 \neq \alpha_4 \neq \alpha_5 \neq \alpha_6 \neq 0$.

The study further adopted the novel dynamic ARDL simulation model proposed by Jordan and Philips (2018) to investigate the counterfactual response in one explanatory variable while others are held constant on the explained variable. Importantly, this empirical procedure improves the complex interpretation of the existing ARDL model. The novel DYNARDL model simultaneously tests the short- and long-nexus between — RSTOCK and exogenous variables (ROIL, RWTI, RCOAL, RNGAS, SHTI, and IPI). The model simulation is also proficient in scrutinizing the effect of actual positive or negative change in the exogeneous variable due to the dynamic nature of the data (Sarkodie and Owusu, 2020). The dynamic ARDL simulation model involves the estimation of the following model:

$$\begin{aligned}\Delta(y)_t = \beta_o + \sum\nolimits_{i=1}^{p} \varphi_i \Delta(y)_{t-i} + \sum\nolimits_{i=1}^{q} \alpha_{1i} \Delta(x_1)_{t-i} + \ldots\ldots + \sum\nolimits_{i=1}^{q} \alpha_{ki} \Delta(x_k)_{t-i} \\ + \theta_1(y)_{t-1} + \theta_2(x_1)_{t-1} + \ldots\ldots + \theta_k(x_k)_{t-1} + \varepsilon_t\end{aligned} \tag{2}$$

Where (y) denotes the dependable variable, (β_o) represents the intercept, (p) denotes the lag order of dependent variable, (q) denotes the lag order of independent variables, (Δ) represents first difference, (x_k) denotes independent variable and (ε_t) represents the error term in time t. The null hypothesis of no level cointegrated relationship is H_o: $\theta_1 = \theta_2 = \theta_3 = \theta_4 = \theta_5 = \theta_6 = 0$, against the alternative hypothesis H_1: $\theta_1 = \theta_2 \neq \theta_3 \neq \theta_4 \neq \theta_5 \neq \theta_6 \neq 0$.

The descriptive statistical analysis elaborating the characteristic of the sampled series is presented in Table 1. It can be observed from the Jarque-Bera test statistics that the sampled series violate the normal distribution assumption, hence, we transformed the variables using logarithmic-data preprocessing technique to control for heteroskedasticity.

3. Results and discussion

3.1. Unit root

We employed unit root tests to examine the properties of the variables using Phillips-Perron (PPERRON) and Augmented Dicky-Fuller (ADF) test to ascertain the order of integration and obtain robust results. Table 2 presents the outcomes of PPERRON and ADF unit root tests (Dickey and Fuller, 1981; Perron, 1989). Evidence from Table 2 shows the null hypothesis of unit root (PPERRON and ADF) of real stock prices (RSTOCK) is rejected at 1% significance level. Based on the PPERRON and ADF unit root tests, we fail to reject the null hypothesis for real oil price (ROIL), real WTI oil price (RWTI), real coal price (RCOAL), real natural gas price (RNGAS), industrial production (IPI), and short-term interest rate (SHTI) at 5% significance level. The log first-difference of all variables reveal a rejection of the null hypothesis of unit root (PPERRON and ADF) at 1% significance level. Thus, while RSTOCK unit root test is I(0) process, ROIL, RWTI, RCOAL, RNGAS, IPI, and SHTI are I (1) processes. Hence, the data series are potential variables for ARDL bounds cointegration.

3.2. Lag selection for ARDL and dynamic ARDL models

The maximum lag selection is the first step for ARDL bound cointegration test. Table 3 presents the vector autoregression selection order criteria (VARSOC) used to select the optimal lag for the model in this study. The likelihood-ratio test statistics (LR), Akaike's information criterion (AIC), Schwarz's Bayesian information criterion (SBIC), and Hannan and Quinn information criterion (HQIC) result are shown in Table 3. Lag 1 is selected as the optimal lag for the model based on Schwarz's Bayesian information criterion, and Hannan and Quinn information criterion.

Table 3
Selection-order criteria for maximum lags.

Lag	LL	LR	DF	P	AIC	HQIC	SBIC
0	4094.1				-24.6217	-24.2346	-24.1937
1	4248.29	308.38	36	0.000	-24.9631	-24.7734*	-24.4871*
2	4308.14	119.71	36	0.000	-25.1047	-24.7523	-24.2205
3	4349.54	82.781	36	0.000	-25.1367*	-24.6216	-23.8445
4	4381.49	63.905*	36	0.003	-25.1127	-24.435	23.4124

Note: * denotes the selected optimal lag using likelihood-ratio test statistics, Akaike's information criterion, Hannan and Quinn information criterion, and Schwarz's Bayesian information criterion.

Table 4
ARDL bound test.

Bound	10%		5%		1%		F/t Statistic
	I(0)	I(1)	I(0)	I(1)	I(0)	I(1)	
F	2.271	3.368	2.641	3.814	3.432	4.745	46.26
T	-2.559	-3.867	-2.86	-4.199	-3.443	-4.821	-12.76

Table 5
Results of ARDL and dynamic stimulated ARDL models

Variables	ARDL Coefficient	DYNARDL Coefficient
ECT LNRSTOCK	-0.5435***	-0.5435***
Standard Err	(0.0426)	(0.0426)
95% Conf. Interval	[-0.6273, -0.4598]	[-0.6273, -0.4597]
Long Run		
ΔLNROIL	-0.0098***	-0.0053***
Standard Err	(0.0015)	(0.0007)
95% Conf. Interval	[-0.0127, -0.0069]	[-0.0066, -0.0040]
ΔLNRCOAL	-0.0037	-0.0020**
Standard Err	(0.0017)	(0.0009)
95% Conf. Interval	[-0.0070, -0.0005]	[-0.0038, -0.0003]
ΔLNRNGAS	-0.0020**	-0.0011***
Std Err	(0.0008)	(0.0004)
95% Conf. Interval	[-0.0036, -0.0005]	[-0.0020, -0.0003]
ΔLNSHTI	-0.0004	-0.0002
Standard Err	(0.0004)	(0.0002)
95% Conf. Interval	[-0.0011, 0.0003]	[-0.0006, 0.0002]
ΔLNIPI	0.0221	0.0120
Std Err	(0.0162)	(0.0086)
95% Conf. Interval	[-0.0098, 0.0539]	[-0.0048, 0.0288]
Short Run		
ΔLNROIL	0.0041***	-0.0012**
Std Err	(0.0005)	(0.0005)
95% Conf. Interval	[0.0031, 0.0051]	[-0.0022, -0.0002]
ΔLNRCOAL	0.0030***	0.0010
Std Err	(0.0007)	(0.0007)
95% Conf. Interval	[0.0016, 0.0044]	[-0.0004, 0.0023]
ΔLNRNGAS	0.0011***	0.0000
Std Err	(0.0003)	(0.0003)
95% Conf. Interval	[0.0005, 0.0017]	[-0.0006, 0.0006]
ΔLNSHTI	-0.0001	-0.0003**
Std Err	(0.0001)	(0.0001)
95% Conf. Interval	[-0.0004, 0.0002]	[-0.0006, -0.0000]
ΔLNIPI	-0.0018	0.0102
Std Err	(0.0066)	(0.0067)
95% Conf. Interval	[-0.0147, 0.0112]	[-0.0030, 0.0235]
Constant	0.5428***	0.5428***
Std Err	(0.0425)	(0.0425)
95% Conf. Interval	[0.4592, 0.6265]	[0.4592, 0.6265]
R-squared	0.4912	0.4912
Adj R-squared	0.4743	0.4743
Mean-squared Err	0.0007	0.0007

Note: ***,**,* denote statistical significance at 1%, 5%, and 10%; parenthesis (..) denotes the standard error whereas square bracket [.,.] denotes the confidence intervals.

3.3. Cointegration

After meeting the prerequisite, the underlining variables employed are said to be a combination of I(0) and I(1). The presence of long-run relationship can be established using the ARDL bounds test co-integration as proposed by Pesaran et al. (2001). We conducted cointegration test to examine the level of relationship of the proposed models. Table 4 presents the ARDL bounds cointegration test (Kripfganz and Schneider, 2020). The cointegration test uses response surface regression with true critical values and approximate p-values. The ARDL bounds cointegration test shows the F-statistics of all level and fist difference variables in the proposed model are extremely above 10%, 5%, and 1% upper critical values and corresponding significant p-values. Hence, the null hypothesis of no co-integrated relationship between real stock index, real oil price, real coal price, real natural gas price, industrial production index, and short-term interest rate is rejected at 10%, 5%, 2.5%, and 1% significant levels in the estimated model.

Table 6
Validated results of ARDL and dynamic stimulated ARDL model

Variables	ARDL Coefficient	DYNARDL Coefficient
ECT LNRSTOCK	-0.6248***	-0.6248***
Standard Err	(0.0448)	(0.0448)
95% Conf. Interval	[-0.7126, -0.5368]	[-0.7128, -0.5368]
Long Run		
ΔLNRWTI	-0.0111***	-0.0070***
Standard Err	(0.0012)	(0.0007)
95% Conf. Interval	[-0.0135, -0.0087]	[-0.0084, -0.0055]
ΔLNRCOAL	-0.0037	-0.0023***
Standard Err	(0.0014)	(0.0009)
95% Conf. Interval	[-0.0064, -0.0010]	[-0.0040, -0.0006]
ΔLNRNGAS	-0.0015**	-0.0009**
Std Err	(0.0007)	(0.0004)
95% Conf. Interval	[-0.0028, -0.0002]	[-0.0018, -0.0001]
ΔLNSHTI	-0.0004	-0.0002
Standard Err	(0.0003)	(0.0002)
95% Conf. Interval	[-0.0010, 0.0002]	[-0.0006, 0.0002]
ΔLNIPI	0.0213	0.0133
Std Err	(0.0137)	(0.0084)
95% Conf. Interval	[-0.0056, 0.0483]	[-0.0031, 0.0298]
Short Run		
ΔLNRWTI	0.0028***	-0.0042***
Std Err	(0.0006)	(0.0006)
95% Conf. Interval	[0.0016, 0.0040]	[-0.0052, -0.0003]
ΔLNRCOAL	0.0030***	0.0007
Std Err	(0.0007)	(0.0007)
95% Conf. Interval	[0.0017, 0.0044]	[-0.0006, 0.0020]
ΔLNRNGAS	0.0011***	-0.0002
Std Err	(0.0003)	(0.0003)
95% Conf. Interval	[0.0005, 0.0017]	[-0.0004, 0.0008]
ΔLNSHTI	-0.0001	-0.0003**
Std Err	(0.0002)	(0.0002)
95% Conf. Interval	[-0.0004, 0.0002]	[-0.0006, -0.0000]
ΔLNIPI	-0.0023	0.0111*
Std Err	(0.0064)	(0.0066)
95% Conf. Interval	[-0.0149, 0.0104]	[-0.0019, 0.0240]
Constant	0.6240***	0.6240***
Std Err	(0.0447)	(0.0447)
95% Conf. Interval	[0.5361, 0.712]	[0.5361, 0.7120]
R-squared	0.5136	0.5136
Adj R-squared	0.4975	0.4975
Mean-squared Err	0.0007	0.0072

Note: ***,**,* denote statistical significance at 1%, 5%, and 10%; parenthesis (..) denotes the standard error whereas square bracket [.,.] denotes the confidence intervals.

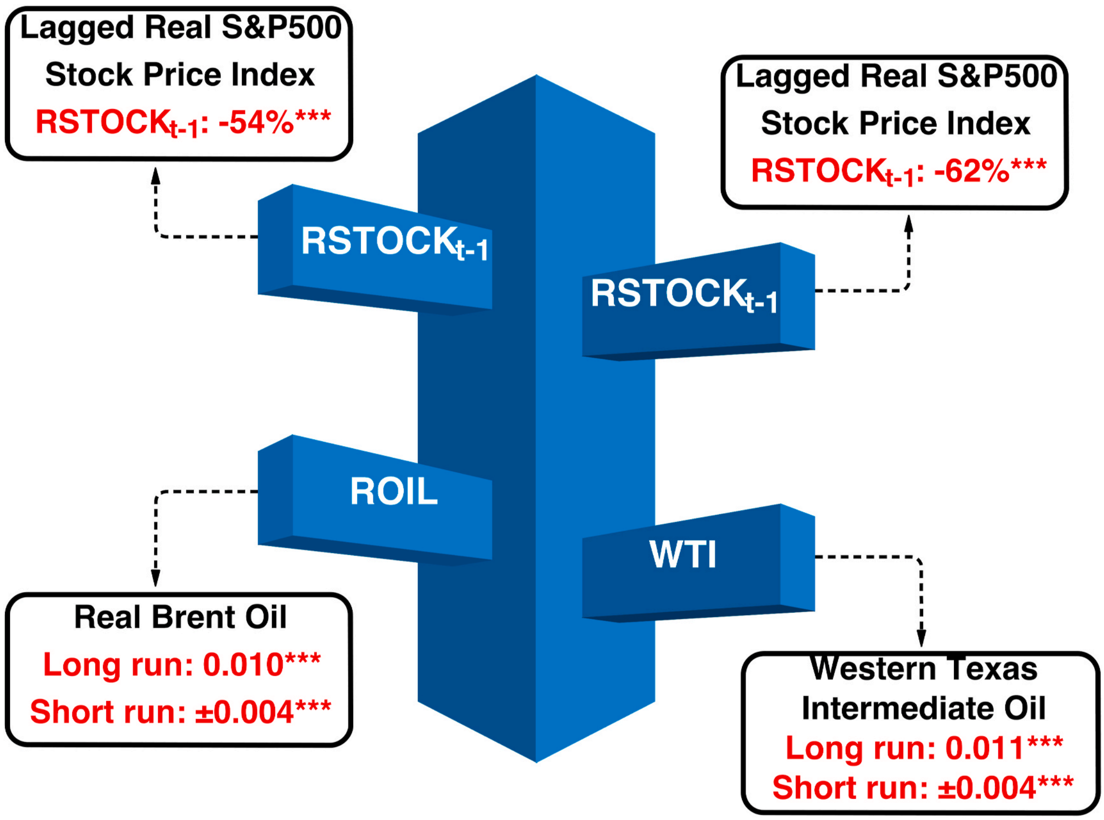
3.4. Validation of estimated model

The ARDL and DYNARDL estimators were used to validate the results presented in Table 5, whereas the validation results of the output parameters in Table 5 are presented in Table 6. Models 3 and 2 were used in the validation of ARDL and DYNARDL simulation to verify the robustness of the models and check sensitivity of the model by substituting real brent oil with WTI oil indicator. The model specification is expressed as:

$$\begin{aligned}\Delta RSTOCK = \beta o + \sum\nolimits_{i=1}^{p}\delta_i \Delta RSTOCK_{t-i} + \sum\nolimits_{i=1}^{q}\delta_{2i}\Delta RWTI_{t-i} \\ + \sum\nolimits_{i=1}^{q}\delta_{3i}\Delta RCOAL_{t-i} + \sum\nolimits_{i=1}^{q}\delta_{4i}\Delta RNGAS_{t-i} + \sum\nolimits_{i=1}^{q}\delta_{5i}\Delta SHTI_{t-i} \\ + \sum\nolimits_{i=1}^{q}\delta_{6i} iIPI_{t-i} + \alpha_1 RSTOCK_{t-1} + \alpha_2 ROIL_{t-1} + \alpha_3 RCOAL_{t-1} \\ + \alpha_4 RNGAS_{t-1} + \alpha_5 SHTI_{t-1} + \alpha_6 IPI_{t-1} + \varepsilon_t \end{aligned} \tag{3}$$

Where β represents the intercept, p is lag order of endogenous variable, q is lag order of exogeneous variables, ε_t is the white noise, and Δ is the difference-operator.

The validation results in Table 6 show the summary of parameters from the ARDL and DYNARDL techniques—where ROIL in models 2-3 is



Scheme 1. Estimated parameters in S&P500 index function with real Brent oil and West Texas Intermediate (WTI) crude oil price, respectively. Note: ***denotes statistical significance at *p-value* < *0.01*.

replaced with RWTI. The results in Table 6 show that the sign and magnitude of the coefficients are quite similar to results presented in Table 5 (see Scheme 1). The estimated error correction term in Table 6 (-0.62) is relatively higher compared to the speed of adjustment in Table 5 (-0.54). This finding depicted in Scheme 1 indicates that replacing ROIL with RWTI oil increases the speed of ECT from 54% to 62%. This infers that the inclusion of real Western Texas Intermediate oil in real stock function corrects historical anomalies in real stocks by 8% faster compared to real Brent oil. Besides, evidence from Scheme 1 reveals that both ROIL and RWTI provide robust and consistent estimates of other regressors in S&P500 index function. The lag-dependent variable of both oil indicators supports the stabilization of stock market vulnerabilities in a long-run relationship. However, the inclusion of RWTI improves the long-run relationship between the dependent variable — RSTOCK, and independent variables — RCOAL, RNGAS. The ARDL bound cointegration test of the null hypothesis of no cointegrated relationship is rejected at 10%, 5%, 2.5%, and 1% significant levels in the estimated model.

3.5. ARDL model

This study presents the ARDL regression model proposed by Pesaran et al. (2001). Table 5 presents the results of ARDL model estimation. All the ARDL estimated coefficients are presented along with their standard error in parenthesis and confidence intervals in squared bracket. The estimated error correction term [ECT (-1)] is -0.543 and significant at 1% level—confirming evidence of long-run equilibrium relationship between real stock market, real oil price, and real natural gas price. The first indication is that an increase in real oil price by 1% stimulates a decline in real stock index by 0.989% at *p-value* < *0.01* whereas 1% increase in real natural gas price decreases real stock index by 0.204% at *p-value* < *0.05*. Though not statistically significant (*p-value*>*0.05*), 1% increase in real coal price and short-term interest rate declines real stock index by 0.372%, and -0.429%, respectively, whereas 1% increase in industrial production index provokes growth in real stock index by 2.21%. Hence, real stock index has negative long-run relationship with real oil price, real natural gas price, real coal price, and short-term interest rate, but positive long-run relationship with industrial production index. Evidence from this study suggests real oil price has superior power than real natural gas in explaining the dynamics of real stock index in the long run. Our finding is in line with existing literature that reported West Texas Intermediate crude oil as better oil indicator in explaining the long-run relationship with the US stock market than other liquid gas (Benkraiem et al., 2018). The study shows that oil price and short-term interest rates have significant negative relationship with stock price, corroborating the empirical results herein (Sadorsky, 1999).

Evidence from the short-run relationship between energy commodities and real stock index differs from the long-run results discussed earlier. Table 5 shows evidence of short-run equilibrium relationship between real energy commodities and real stock index. The empirical evidence shows that 1% increase in real oil price, real coal price, and real natural gas price increases real stock index by 0.41%, 0.30%, and 0.11%, respectively at 1% significance level. The short-term interest and industrial production index exhibit statistically insignificant short-run positive relationship with real stock index. Increasing short-term interest rate and industrial production by 1% simulates a decline in real stock index by 0.007% and 0.177% respectively. The evidence of positive short-run relationship between real oil price, real coal price, real natural gas price, short term interest rate, and industrial production may be due to inefficient financial market—where a change in the price of energy commodities and economic activity is not immediately transmitted to the stock market index but leads to lagged-decline in stock market prices. One will expect that traders and asset managers in the US financial market will quickly react to information attributed to oil and natural gas

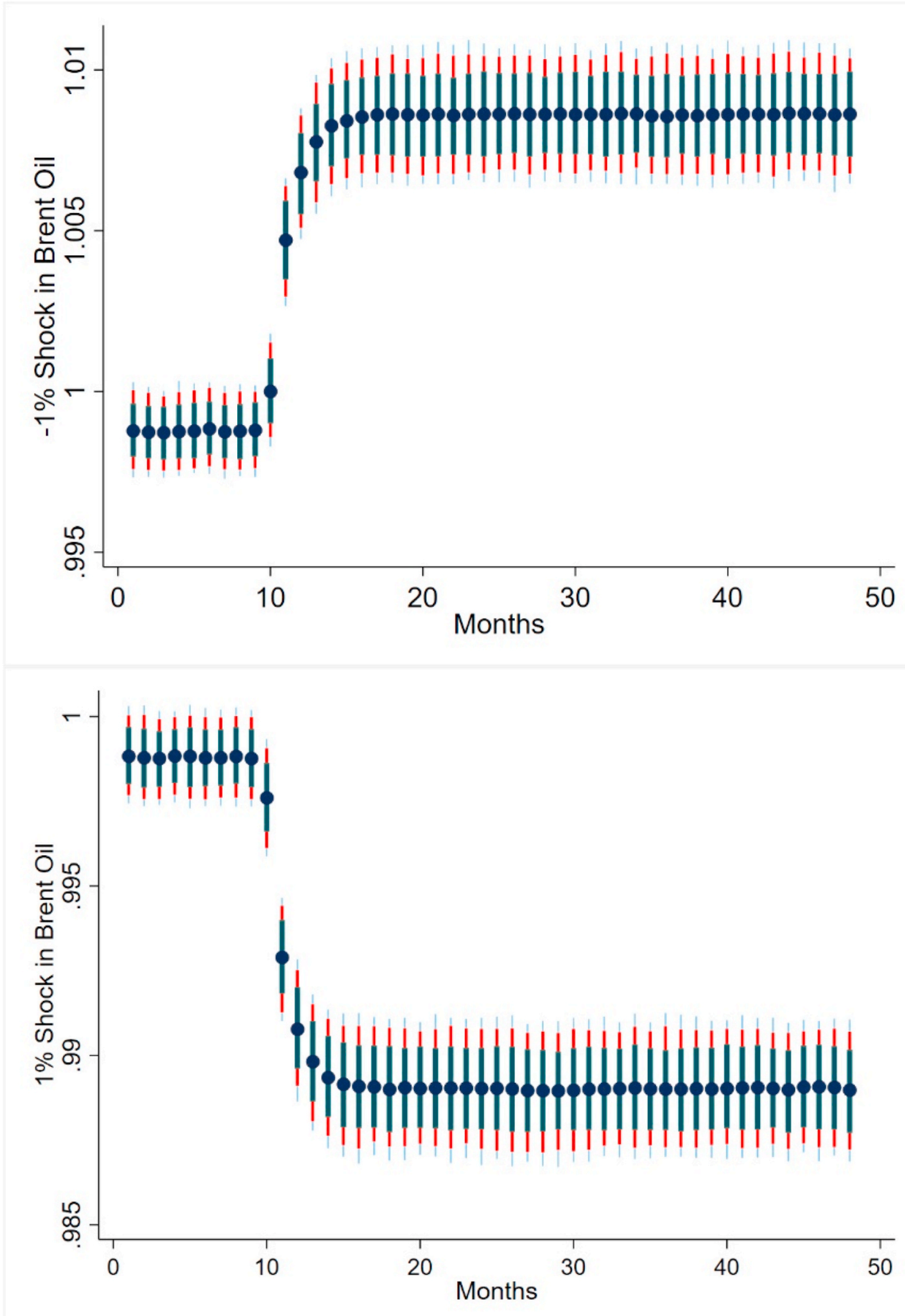


Fig. 2. Counterfactual shock in Brent Oil.

price changes, and to rapidly transmit the shocks to stock market prices. Surprisingly, that is not the case from our study—implying that investors react less quickly to changes in the price of oil, coal, and natural gas in the short run. However, some findings from previous studies reveal negative relationship between West Texas Intermediate (WTI) crude oil price, natural gas price, and S&P500 index in the short run (Benkraiem et al., 2018). The study further indicates oil price has statistically significant impact on monthly US stock market using the multivariate VAR model (Park and Ratti, 2008).

3.6. Dynamic ARDL model

We applied the novel dynamic stimulated ARDL model proposed by Jordan and Philips (2018) in examining the short-run and long-run relationship and energy commodities price shock on the real stock market by estimating coefficients, stimulating meaningful response, and automatically plotting predictions of counterfactual changes in one endogenous variable based on *ceteris paribus* assumption. The dynamic simulations show the impulse-response of an endogenous variable held constant overtime to given shocks from the exogenous variables. The data series employed must meet the prerequisite conditions before applying the dynamic stimulated ARDL technique, the model estimated coefficients should be stationary, I(1), and cointegrated. The dynamic ARDL error correction algorithm for the model created 1000 simulations across 48-time points (months) after validating sampled variables meet the requirements.

Table 5 presents the results of the dynamic stimulated ARDL technique and further predict the counterfactual response in regressors using

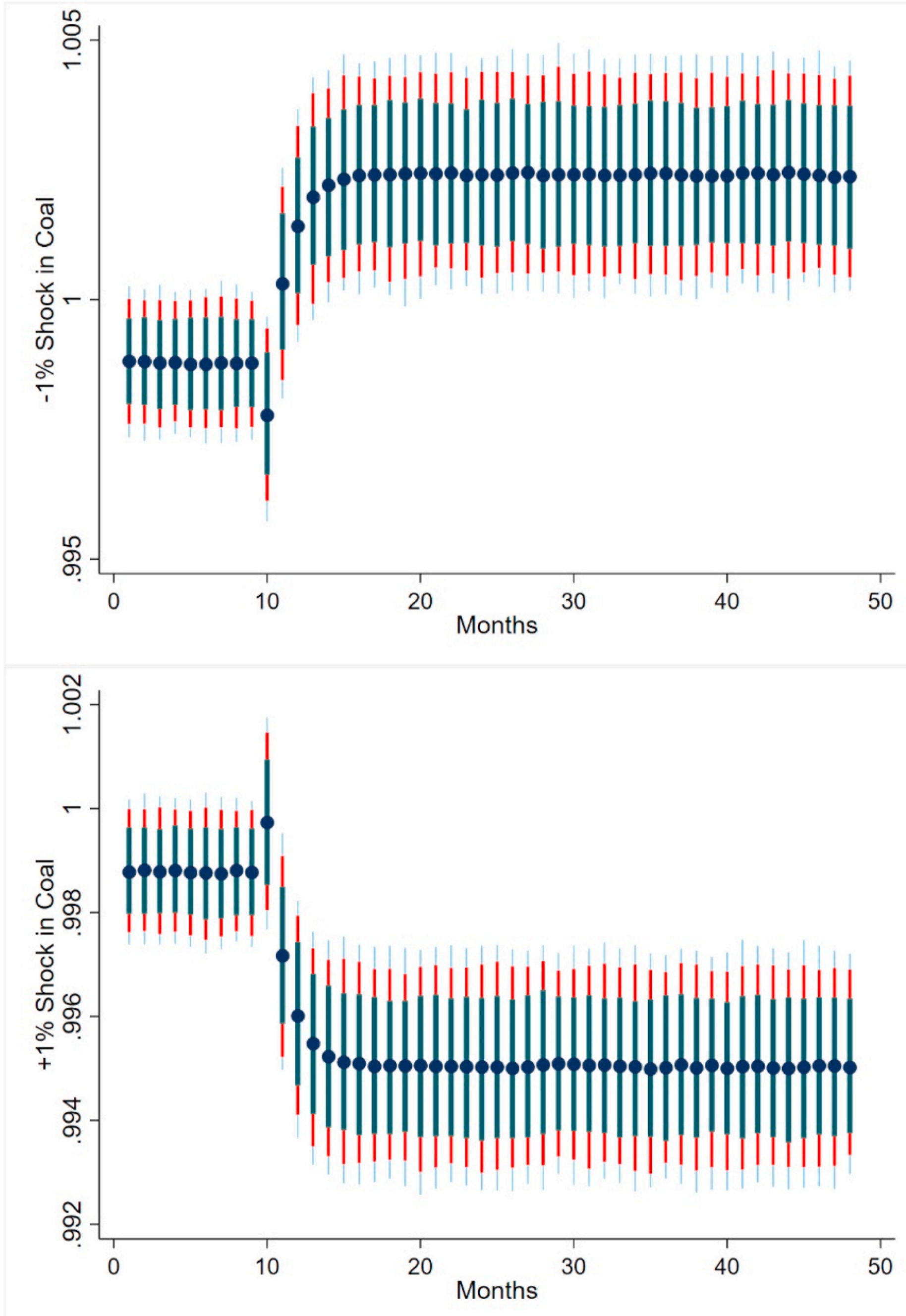


Fig. 3. Counterfactual shock in Coal.

graphical representation. Energy commodities such as oil, natural gas, and coal play a critical role in the global financial market of oil-importing and exporting countries as outlined by the International monetary fund. This study presents the counterfactual shock by simulating average responses that reveal the interaction between exogenous and endogenous variables. From Table 5 column 3, the model reveals error correction — -0.544 representing 54.4% speed of adjusting past disequilibrium over time—as the variable stabilizes over a long-run relationship. We observe a statistically significant negative long-run relationship between the stock index and the three energy commodities. The coefficient on the real oil price and real natural gas price recorded -0.53% and -0.20% at 1% significant level—indicating a 1% increase in real oil price and real natural gas price will provoke a decrease in real stock index in the long-run. The real coal price exhibits a negative coefficient, indicating a 1% increase in it will result 0.20% decrease in real stock index at 5% significance level. The study reveals a negative and positive long-run relationship for short-term interest rate and industrial production index, but insignificant to make statistical inferences. Evidence from this study is similar to the results of ARDL model presented herein—that found a negative relationship between real stock index and real oil price, real coal price, real natural gas price, and short-term interest—but a positive relationship with industrial production index in the long run. It is consistent with the study that presented evidence of significant negative relationship between stock index and oil price, natural gas in the long run (Sadorsky, 1999).

Table 5 column 3 presents empirical evidence that reveals a negative short-run relationship between real stock index and real oil price, real natural gas price, real coal, short-term interest rate, and industrial

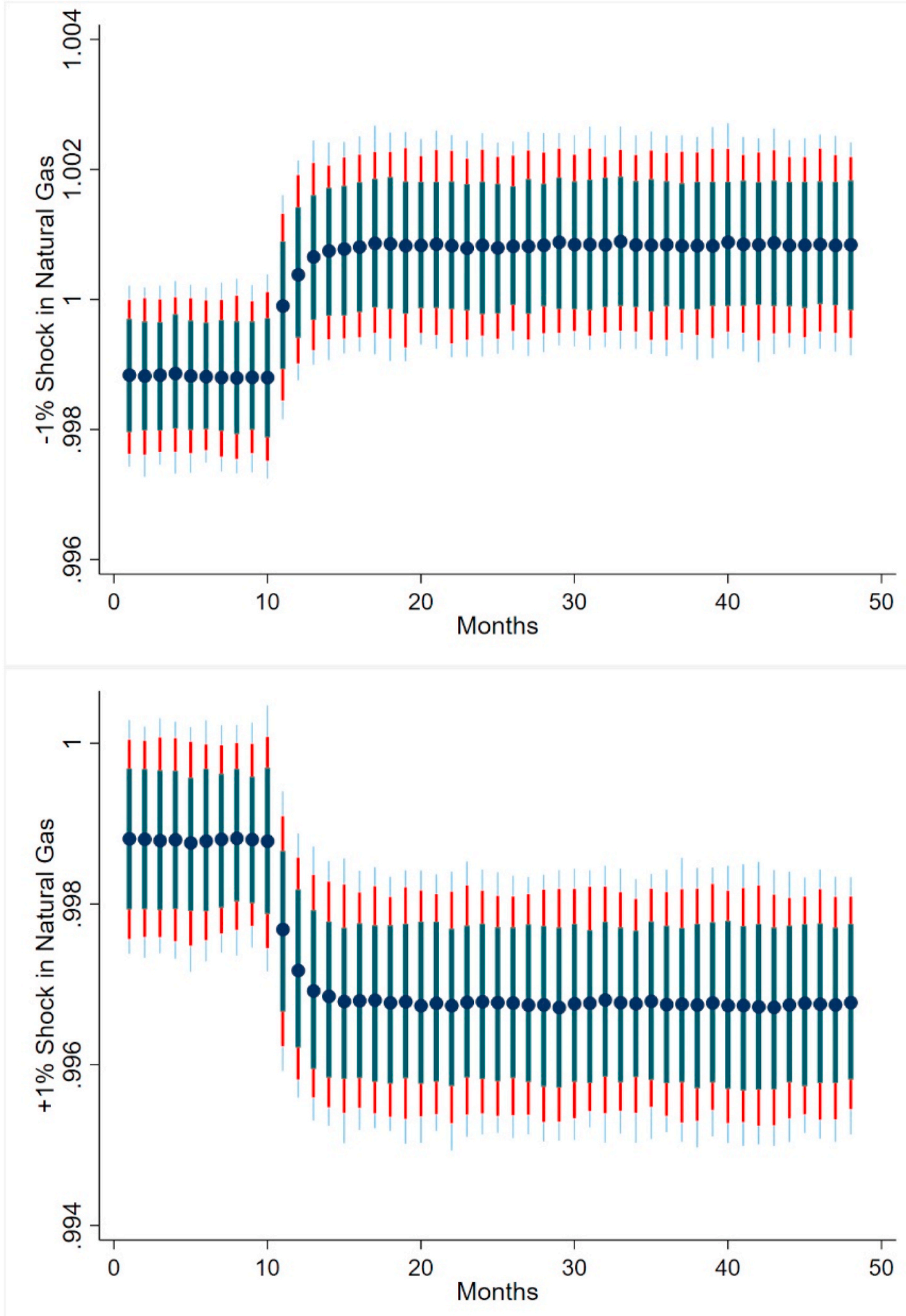


Fig. 4. Counterfactual shock in Natural Gas.

production index. Growth in real oil price and short-term interest rate by 1% declines real stock price by 0.12% and 0.03%, respectively at *p-value* < 0.05. Though real natural gas price and industrial production index shows insignificant negative coefficients, however, 1% increase in real natural gas price and industrial production index decreases real stock index by 0.003% and 1.02% respectively. Evidence of the negative short-run response of real oil price and real natural gas can partly be attributed to portfolio managers' reaction to the future uncertainty of global crude oil supply and demand, given the volatility due to political unrest and terrorism in some oil-producing countries in the Middle East and Africa. The real coal price is the only exogenous variable that shows a positive short-run relationship with real stock price, but with insignificant statistical inference.

Figs. 2-6 depict the impulse-response plots from the dynamic ARDL model showing the relationships of a shock on real oil price, real coal price, real natural gas price, short term interest rate, and industrial production index and their possible contemporary effect on real stock index. Fig. 2 shows that a +1 shock in real oil price increases real stock index till the 9th time scenario in the short run and eventually trend downwards from the 10th time scenario and stabilizes in the long run. Alternatively, -1 shock produces a stable positive effect in the short run but increases from the 10th time scenario and stabilizes in the long run. This result is consistent with the notion that fear of inflation pressure is closely associated with positive shock in global oil price—as is vital commodity for production, hence, increasing the total production cost can cause a decline in earnings—dampening the stock market price. The negative shock has a positive effect on the economy by reducing the cost of production for companies with oil as major production cost. When the

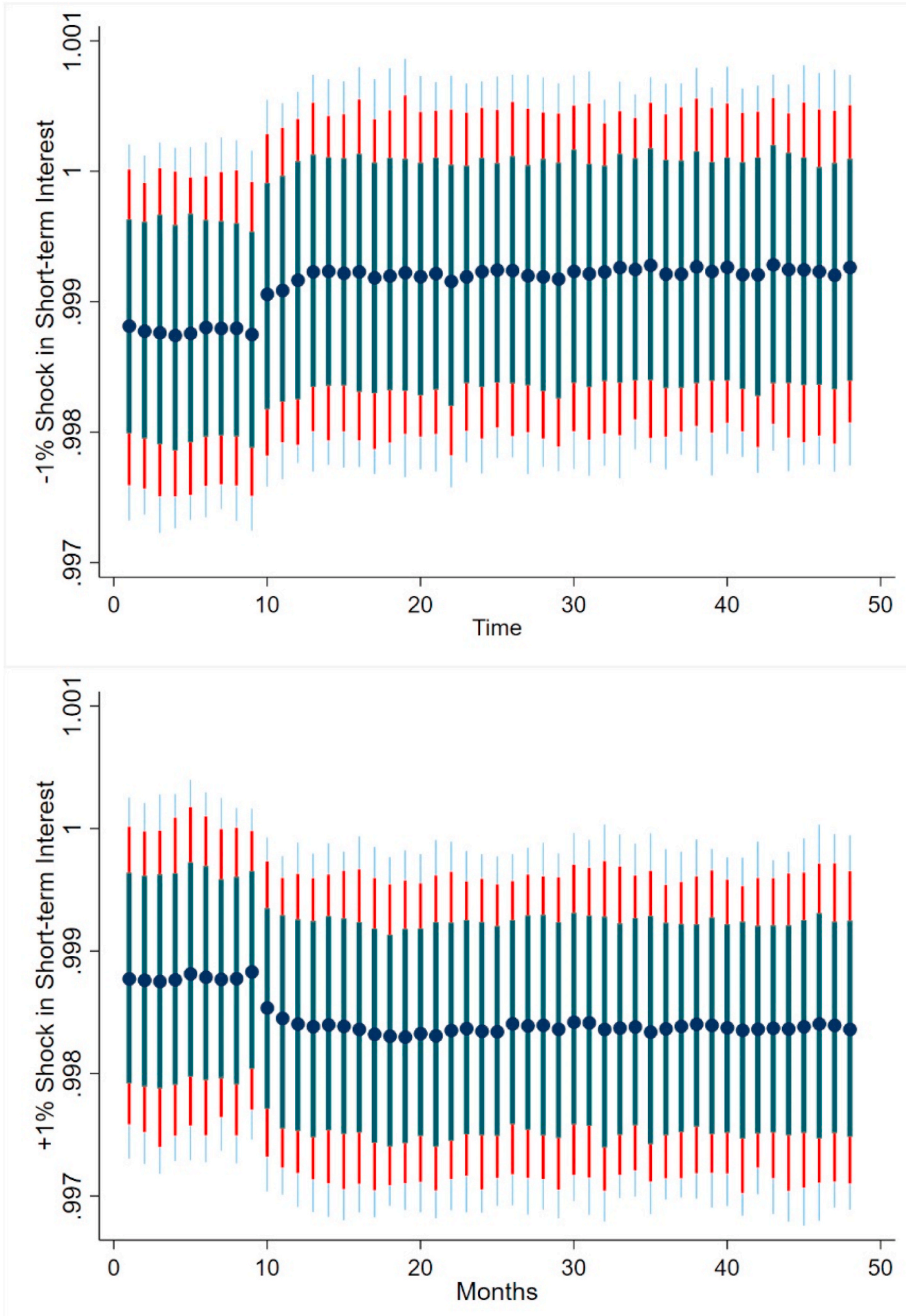


Fig. 5. Counterfactual shock in Short-term Interest.

market is efficient, a positive or negative price shock in oil price will cause an immediate decline or rise in the stock market index. In contrast, with inefficient market, a positive or negative shock in oil price will cause a lagged decline or rise in the stock market index as a witness in this study. This result is line with other studies (Benkraiem et al., 2018; Park and Ratti, 2008; Sadorsky, 1999). Nevertheless, our results are contrary to reported studies that indicate great oil price shock does not affect or influence the US stock market index (Alsalman and Herrera, 2015).

Fig. 3 shows a positive shock in real coal price increases real stock index in the short run but eventually decline from the 11^{th} scenario and stabilizes in the long run of 48 scenarios. On the contrary, a negative shock in real coal price slightly increases real stock index in the short run but increases at a higher rate from the 11^{th} scenario and later stabilizes in the long run.

Fig. 4 reveals that a positive shock in real natural gas price triggers an increase in real stock index in the short run and declines from the 10^{th} scenario but stabilizes over the long run scenario of 48 months. However, a negative shock increases real stock index slightly in the short run but increases at higher level in the long run from $t = 11$. The global traders and financial analysis especially in the US, adopt natural gas and crude oil as the two most important economic variables in forecasting future stock market prices. Evidence from this simulation indicates that investors react quickly to the changes in the price of natural gas—as the shocks are spread swiftly to stock market index in the short run and this is consistent with the finding of Benkraiem and Lahiani et al., (2018).

Fig. 5 shows that a positive shock in short-term interest rate has a negative effect on real stock index in the long-run, but a positive effect at

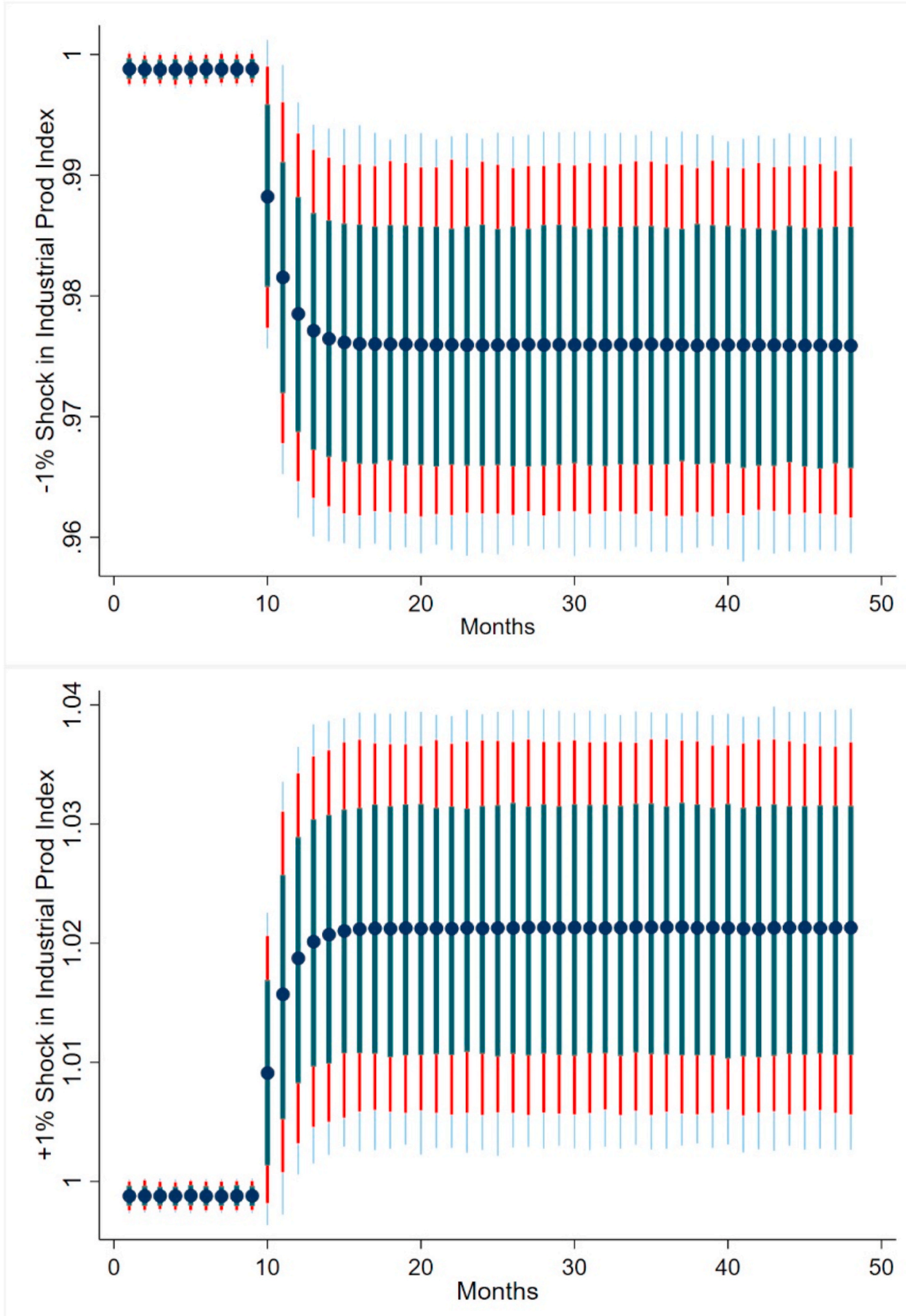


Fig. 6. Counterfactual shock in Industrial Production Index.

lower rate in the short-run. The +1 shock increases real stock index slightly in the short run, but declines (t = 10) at a low level of volatility throughout the long-run period (t = 48). Contrary, -1 shock in the short-term interest rate stimulate fluctuations at lower rate in the short run, but eventually increase at higher rate in the long run from t = 10. The changes in interest rate have a direct impact on the changes in the cost of equity—which indirectly affect the corporate turnover and influence the price at which the investor is willing to pay for stock or equity. Consequently, an increase in the cost of equity or debt causes a decline in the stock market index. This empirical evidence is consistent with previous findings (Park and Ratti, 2008; Sadorsky, 1999).

Fig. 6 reveals that an increase in industrial production generates economic growth and strong performance. Stronger economic performance implies high earning by companies and high dividend payments to shareholders which drive stock market prices up. This theory is confirmed by evidence from our study that shows stochastic simulation of +1 shock in industrial production index increases real stock index below the predicted value in the short run but increase (t = 10) above the predicted value and stabilizes in the long run. Alternatively, the -1 shock triggers a slight increase in real stock index in the short run and decreases in the long run thereafter (t = 10).

4. Conclusion

This paper used both ARDL and stochastic simulated ARDL models to investigate the movement in energy commodities, economic activity, and their impact on real stock index. The inflationary pressure in the economy is associated with increased energy prices especially oil price, which has a repeal effect on the cost of equity and investment in all economic sectors. Results from the ARDL model confirmed a negative significant relationship between real oil price, real natural gas price, and real stock index in the long run. An insignificant long-run negative relationship is established between real coal price, short term interest rate, and real stock index. In the short-run ARDL result, the movement in the real price of energy commodities has a significant positive relationship with real stock index.

The results from the dynamic ARDL model found a negative statistically significant long-run relationship between the price movement in energy commodities and real stock index. The short-term interest rates and industrial production index recorded a negative and positive relationship with real stock index in the long run with no statistical inference. Besides, there was evidence of a negative short-run relationship between real oil prices, real natural gas, and the real stock index. The empirical evidence established a positive relationship between real coal price and industrial production index with real stock index with no statistical inference. Evidence from dynamic ARDL simulation found the movement in the price of energy commodities and economic activity is important in explaining the counterfactual changes in real stock index. Empirical evidence of the estimated results underscores positive shock in the price of real oil, real coal, and real natural gas dampen real stock index while a positive shock in the short-term interest rate and industrial production index provokes an increase in real stock index. The negative shock in real oil price, real coal price, and real natural gas price escalates real stock index. Contrary, a negative shock in short-term interest rate and industrial production index hampers real stock index of the US economy. The interest rate, which directly impacts the cost of capital and influences the purchasing power of investors, coupled with a fall in industrial production will halt economic growth and performance — which have adverse effects on long-term economic growth.

Results from this study show energy commodities can be considered as instrument for portfolio diversification and hedging in the long run to minimize the risk exposure—as these assets have negative response to the US stock market. However, the ARDL short-run indicates energy commodities have no power in diversification and hedging as they exhibit influence on the stock market. The short run estimates of dynamic ARDL model exhibit significant negative relationship with the US stock movement—indicating the hedging potential of real oil price. The portfolio and asset managers that participate in the US financial market could pay more attention to historical data on energy commodities, especially crude oil and natural gas due to the volatility in the market using effective models such as dynamic ARDL that adopts multivariate stochastic simulations for prediction to formulate effective risks management policy and accurately predict the future price movement on the market. The findings from investigating energy commodities will inform policymakers on effective strategies in implementing the green agenda such as environmental tax without adverse impact on the US stock market. Regulators can implement policies based on the findings of short-term interest rate and stock market movement using monetary policy to monitor and influence the US stock market. Finally, the financial market participants should be aware of the continuous dynamic relationship between energy commodity prices and stock market, and accordingly, formulate a strategy to counter it.

Author contributions

M.Y.A: Conceptualization; Data curation; Writing – original draft; Software; Validation; Writing – original draft. S.A.S: Conceptualization; Funding acquisition; Software; Visualization; Writing – original draft; Writing – review & editing.

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.

Acknowledgment

Open Access funding provided by Nord University.

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