Appraising the oil–stock nexus during the COVID-19 pandemic shock: a panel threshold analysis

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Abstract

We examine the oil–stock nexus in 24 countries amidst the COVID-19 pandemic and test for threshold effects on oil prices using Hansen (1999) panel dynamic threshold model and recent extensions of Kremer et al. (2013) and Seo and Shin (2016). We find evidence of nonlinearities and threshold effects in oil prices. As an addition to literature, our estimated model shows that stock market prices react in a regime-style manner, when the joint effects of oil prices, exchange rate changes, number of reported cases, and the number of death due to COVID-19 pandemic are analyzed. This is in support of the theoretical model of investor sentiment by Barberis et al. (1998). Therefore, we are of the opinion that policymakers, governments, and investors in their business decision-making process should put into consideration and also observe changes in the global reported cases alongside the number of deaths and how oil prices are evolving, as the global economy is further affected by the COVID-19 pandemic shock.

Keywords COVID-19 · Oil prices · Stock price and panel threshold analysis

JEL classification C23 · E44 · G15 · I12 · Q43

Introduction

The current coronavirus outbreak, initially of unknown etiology, originated from Wuhan City, China, in a wholesale fish and live animal market. The infection subsequently spread to other countries almost immediately and has been reported in almost all the countries of the world. The World Health Organization (WHO) which initially declared it a “public health emergency of international concern” later confirmed it as a “global

pandemic” because of its spread. The coronavirus pandemic has distorted the economic, social, political, religious, and financial architecture of the entire world. Global stock markets have taken a major hit by the pandemic as well. Indeed, the pandemic has presented the world economy in the most difficult situation that can only be compared to what happened during the World War 2.

The pandemic has led to lockdowns by governments around the world in a bid to curb its spread. The lockdown actions have led to the closure of production hubs leading to a drop-in demand for energy and the subsequent crash in oil prices. The fall in oil prices also affected the financial sector. Even though the disease started in December 2019, markets did not react negatively until February 2020, when stock markets around the world faced their worst week since 2008 financial crisis. The US stock market lost nearly 12% of their stock values, MSCI's World Index was 10% down, European Shares lost roughly 1.5 trillion US dollars, and the Asian stock incurred significant losses (Hassan et al. 2020).

Since the pioneering work of Hamilton (1983) investing the link between oil prices and the macroeconomy has been

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of great importance (see Hamilton 2003 & Bachmeier 2008). Ciner (2001) establishes the nonlinear effects of oil prices on economic activity. According to him, contending the increase in oil prices retards economic activity¹. Furthermore, several studies have attempted to shed light on the effect of oil price on stocks, primarily through their impact on future cash flows of firms (see Chen et al. 1986; Jones and Kaul 1996; Sadorsky 1999; Papapetrou 2001; Hammoudeh and Li 2005; Ghouri 2006; Hammoudeh and Choi 2007; Nandha and Hammoudeh 2007; Park and Ratti 2008; Henriques and Sadorsky 2008; Narayan et al. 2010; Wang et al. 2013 and Salisu et al. 2019², Alola 2020a, b.) Understanding the oil–stock nexus is crucial. Oil serves a critical input in firm’s production cost, and hence, movements in oil price will have an effect on firms expected cash flows influencing earnings and dividends and consequently the stock price of a firm (Rafailidis and Katrakilidis 2014).

The interaction between oil–stock nexus has been stated to be of an important subject in understanding firm’s production cost, profits, and eventually the overall performance of such an economy. Thus, it is paramount to examine how the COVID-19 cases and its attendant deaths rate affects demand–supply of oil prices and its extended impact on the movements of stock prices, as movement in stock prices can act as an early warning signal for the direction of the economy. We are of the opinion that, increased COVID-19 cases have the tendency to causing fluctuation in economic activities, thereby affecting oil prices. As more economies of the world embark on lockdowns as a measure of curtailing the virus, demand for oil decreases, while production becomes moderate or increases, this would eventually facilitate movements of stock prices as investors move to save their investment in more suitable and efficient portfolio against the effects of the pandemic.

In addressing the level of uncertainty created by the COVID-19 pandemic on oil price co-movements, Akhtaruzzaman et al. (2020) in their study, titled “COVID-19 and oil price risk exposure of both financial and non-financial sectors,” argued that oil users or industries suffer most in terms of benefit when there is a decrease in oil prices. According to the literature (see Elyasiani et al. 2011), most financial sectors are negatively exposed to oil price risk. Although, the financial sectors are not directly users of oil or involved with oil production, their association with oil occurs mainly via lending and investment portfolios to firms, which have exposure to oil price risk. Lending from Forbes (2018),

the breakdown of bank loan portfolios shows that the majority of loans go to individuals and industries other than oil and gas industry. The relative higher exposure to oil-user industries leads to the negative exposure of these sectors to oil price risk. This is in line with the study of Samadi et al. (2021) for Iran, where they argued that the period COVID-19 pandemic outbreak created uncertainty and more confusion among investor.

In addition, the COVID-19 pandemic has generated interest on how movements in oil prices affect equity markets. Salisu et al. (2020) provided a preliminary analysis on the behavior of oil and stock prices during the COVID-19 pandemic. Result shows that oil and stock markets may experience greater initial and prolonged impact of own and cross shocks during the pandemic than the period before it. In support, Salisu et al. (2020), Albuлесcu (2020), and Zhang et al. (2020) findings show that, as result of the pandemic, market risks has increased. Furthermore, Ashraf (2020) examines stock markets to check if they are sensitive to COVID-19 cases or deaths in 64 countries. The finding shows that stock returns decline as cases of COVID-19 increase. In line with these studies, Alola et al. (2020) and Alola and Victor (2020) concluded that COVID-19 pandemic have a significant impact on both the financial market and environmental sustainability targets, as a result of higher volatility index observed.

Against this backdrop, our main objective in this study is to explore how global stocks are responding to the COVID-19 pandemic and examine the existence of threshold effects following the Hansen (1999) study, using oil prices. We consider the sample period January 2020 to July 2020 as important as this was when the effect of the COVID-19 pandemic was more pronounced, with majority of the global economy experiencing lockdowns at a similar point in time.

A panel examination of the oil–stock nexus is key as there are few panel studies on the topic (see Ramos and Veiga 2013; Gupta 2016). Most of the literature on the oil–stock nexus concentrates on individual countries (time series) especially the USA. We are of the opinion that conducting a panel analysis will aid in identifying effects that may be systematic across countries rather than country specific. Panel dynamic threshold (PDT) regression models specify that individual observations can be divided into classes based on the value of an observed variable. Thus, we are of the opinion that the shocks emanating from the pandemic will adversely alter the oil price–stock nexus. Information about the behavior of the nexus in this difficult time is important for investment and policy decisions as policymakers are confronted with the choice between containing the virus and sustaining the economy.

This study contributes empirically and methodologically to literature. First, our findings reveal there are threshold effects of oil price changes on stock returns. This is consistent with the findings of Barberis et al. (1998) who contends that stock returns move between a stationary and nonstationary regime. Hence, oil price during the COVID-19 pandemic have had

¹ Proposed reasons for the asymmetry include (i) adjustment costs stemming from sectoral imbalances Hamilton (1988), (ii) the undesirable relationship between uncertainty and investment (Bernanke 1983; Ferderer 1996), (iii) monetary policy Bernanke et al. (2004), and (iv) coordination difficulties among firms Huntington (2001).

² For a more exhaustive view of the oil–stock literature, see Smyth and Narayan (2018)

different effects on stock returns in the two regimes as confirmed by our empirical results. Second, the findings reveal that the oil–stock nexus behaves differently when the oil price is above or below the threshold is consistent with the dynamics and structure of the oil industry. As the oil industry is highly capital intensive, when the oil price is above a certain threshold, high cost producers entering the market affect the price of oil. The cost structure of the oil industry can thus give rise to different effects for the relationship between oil and stock prices.

The rest of the paper proceeds as follows: the second section presents the empirical model briefly. The third section presents empirical results of analyses. Lastly, the fourth section concludes the study.

Empirical model

Data

Using daily data from January 2020 to July 2020 for stock, oil price, exchange rate, and COVID-19 cases and deaths, a panel of 24 countries was constructed for the analysis. All data for the analysis was sourced from Bloomberg except for COVID-19 deaths and cases, which were sourced from the European Centre for Disease Prevention and Control (ECDC) (Table 1).

Model

Heterogeneity is a common problem of panel data as the classical fixed effect or random effect model reflects only the heterogeneity in intercepts. The threshold model captures the structural break in the relationship among variables and is popular for modeling nonlinearities in time series (see Tong 1983; Rousseau and Wachtel 2009; Girma 2005). A problem at the heart the threshold regression is in determination of the threshold value. The threshold value must be estimated; meaning standard economic theory and inference are not valid. Hansen (2000) makes a seminal contribution by offering a distribution theory, which permits accurate inference on threshold models.

Following Hansen (1999), we construct a single-threshold model as:

$$SP_{i,t} = \theta_i + X_{i,t}(\phi_{i,t} < \lambda)\beta_1 + X_{i,t}(\phi_{i,t} \geq \lambda)\beta_2 + \varepsilon_{i,t} \quad (1)$$

i represents different countries and t represents different time periods. $SP_{i,t}$ represents stock prices, and θ_i captures the fixed effect; this captures the heterogeneity of stock prices. $X_{i,t}$ is a vector of variables hypothesized to impact stock prices, $\phi_{i,t}$ is the oil price which is the threshold variable, λ is the threshold parameter for the oil prices which divides Eq. (1) into two regimes β_1 and β_2 depending on whether the

Table 1 Variable description. Index represents the relative stock market for the country and all currencies are benchmarked against the US dollar

Country	Proxy
Belgium	Bel-20 index and USD-EURO
Brazil	IBOVESPA index and USD-REAL
Canada	S&P/TSX index and USD-CAD
Chile	S&P/CLX IPSA index and USD-CLP
China	SSE Composite Index and USD-YUAN
France	CAC40 index and USD-EURO
Germany	DAX index and USD-EURO
India	S&P BSE SENSEX index and USD-RUP
Indonesia	Jakarta Composite Index and Rupiah
Ireland	ISEQ 20 index and USD-EURO
Italy	FTSE MIB index and USD-EURO
Japan	NIKKE 225 index and USD-YEN
Mexico	S&P/BMV IPC and USD-PES
Netherlands	AMX index and USD-EURO
Nigeria	NSE index and USD-NGN
Peru	S&P/BVL Peru index and USD-Sol
Portugal	PSI 20 and USD-EURO
Russia	MOEX index and USD-RUP
South Africa	JALSH index and USD-ZAR
Spain	IBEX 35 index and USD-EURO
Sweden	OMX 30 index and USD-SEK
Switzerland	SMI index and USD-CHF
Turkey	BORSA Istanbul 100 Index and USD-LIRA
UK	FTSE 100 and USD-GBP
Oil	Brent Crude (USD)

threshold variable, $\phi_{i,t}$ is smaller or larger than the threshold parameter λ , and $\varepsilon_{i,t}$ represents the errors which is assumed to be identically distributed with a mean of zero and a finite variance $\varepsilon_{i,t} \sim iid(0, \sigma^2)$. Equation (1) can also be written as

$$SP_{i,t} = \theta_i + X_{i,t}(\phi_{i,t}, \lambda)\beta + \varepsilon_{i,t} \quad (2)$$

where

$$X_{i,t}(\phi_{i,t}, \lambda) = \begin{Bmatrix} X_{i,t}I(\phi_{i,t} < \lambda) \\ X_{i,t}I(\phi_{i,t} \geq \lambda) \end{Bmatrix} \quad (3)$$

where $I(\cdot)$ is an indicator function.

Given λ , the ordinary least squares estimator for β is $\hat{\beta} = \{X^*(\lambda)'X^*(\lambda)\}^{-1}\{X^*(\lambda)'SP^*\}$ where SP^* and X^* are within-group deviations and the sum of square residuals (RSS) is $\hat{\varepsilon}^*\hat{\varepsilon}^*$, to estimate the threshold parameter λ for the oil price. A grid search can be computed such that the search occurs within a range of intervals $(\lambda, \underline{\lambda})$ which are quantiles of $\phi_{i,t}$. The obtained λ is the value that minimizes the sum of

square residuals $\hat{\lambda} = \operatorname{argmin} S_1(\lambda)$. Once the sample-splitting value of λ is identified, the estimates of the slope parameters are readily available.

The next problem is to determine whether the threshold variable is significant. If the threshold parameter λ is known, the model is identical to the ordinary linear model. Conversely, λ is unknown, and the potential λ estimators become nonstandard. Hansen (1999) addresses this issue by proving $\hat{\lambda}$ is a consistent estimator for λ , contending the best way to examine if $\lambda = \lambda_0$ is using confidence intervals for λ to form the no-rejection using the likelihood tests on λ . The given the threshold variable is not distinguished under the null hypothesis of an existence of no thresholds. Hence, the Lagrange multiplier (LM) test will be invalid, as critical values cannot be read off standard χ^2 distribution tables. However, Hansen (1999) provides a solution of approximating the critical values using bootstrapping techniques. Consequently, we bootstrap the P value for the heteroscedasticity-consistent LM tests. The bootstrap-dependent variable is generated from the distribution $N(0, \hat{\varepsilon}^2)$ by fixing the regressors. Here, $\hat{\varepsilon}$ is the residual from the estimated threshold model (1).

If a threshold effect is found (i.e., $\lambda \neq \lambda_0$), it is important to form a confidence interval of the critical oil price. Thus, one needs to test for the threshold value as testing for the threshold effect is the same as testing for whether the coefficients are the same in each regime of the threshold variable.

$$\begin{cases} H_0 : \beta_1 = \beta_1 \\ H_1 : \beta_1 \neq \beta_1 \end{cases} \quad (4)$$

A model with a second or higher order threshold can be estimated through extending the model described above in a straightforward fashion.

Empirical results

This section is organized into three subsections. We present and discuss some preliminary analysis with exploratory data analysis to explore the dynamic relationship between stock prices and the COVID-19 pandemic shock in the first subsection. This is particularly important for understanding the modeling approach and inferential expectation of the research. In the second subsection, models' estimations are presented and discussed while battery of diagnostic tests for evaluating the performance of the model is presented in the last subsection.

Some preliminary and exploratory data analysis

In this section, we report the summary statistics of the variables used in the analysis. For the sampled countries, the key

variables are the stock market price, the number of death due to COVID-19 (henceforth, simply *COVID*) and the number of reported cases of COVID-19 (henceforth, simply *cases*). Additional information used in constructing the model is the oil prices and exchange rates, which are proxy for exogenous variables. From the summary statistics presented in Table 2, we can infer that there is an evidence of unpredicted changes in the dynamics of stock prices, COVID, and cases. For example, the estimates of the standard deviation of the stock price almost double the mean estimates. This may suggest that stock prices are characterized with extreme value observation (with excess kurtosis and large asymmetries). Equally, the standard deviation of the cases and COVID are much higher than their mean values, which further underscore the presence of uncertainty within the sampled countries.

Further scrutiny of Table 1 produces evidences of highly nonlinear movement of the variables in the panels which may suggest that the models to be estimated are capable of dealing with nonlinearities. We can also conclude that the large size of standard deviation relative to the size of mean may also suggest that the variables are highly unpredictable.

We visualize the dynamic conditional correlation between the stock prices and cases in Figs.³ 1 and 2. We can readily infer that, from Fig. 1, when the number of reported cases daily in the European countries spiked up to approximately 10,000 (per day), stock prices is observed to fall significantly despite the fall in the number of daily reported cases (as low as less than 3000 cases). This may reflect the increased fear of the investors even with fall in the number of reported cases. However, when the number of daily reported cases stabilizes between the ranges of 3000 and 5000 cases, the stock prices recover mildly and remain much lower than its initial level. Deducing from Fig. 2, which is the case of Latin American countries, we can say that the dynamic interrelationship between the stock prices and the number of daily report cases exhibit strong correlation. Observing from the Fig. 2, with the rise of daily reported cases, slightly above 2000 cases, the stock prices stabilize to the average value of 4000 approximately. With falling number of daily reported cases, as low as 300 cases, the stock price is observed to have increased (by more than 5000 value, see Appendix Figs. 8 and 9).

In the case of Asia, the dynamic correlation between the number of daily reported cases and stock prices is not very discernible as for the dynamic conditional correlation between the stock prices and number of daily reported cases. From Fig. 3 (see Appendix Fig. 10), we can see that the resurgence and gradual increase of daily cases have collapsed the stock prices in the Asian market. There are evidences that rising cases have dampened and crashed down stock prices. This indicates that

³ For visual graph of Africa and North America, the reader is referred to the Appendix section.

Table 2 Summary statistics of the key variables in the panels

Variable		Mean	Std. Dev.	Min	Max	Observations
Stock	Overall	19,345.77	27,574	404.1	123,556.1	$N = 2952$
	Between		27,811.92	540.8076	106,972.3	$n = 24$
	Within		4335.951	− 9829.469	46,128.53	$T = 123$
Cases	Overall	2196.59	4963.6	− 29,726	54,771	$N = 2952$
	Between		3207.412	33.84553	14,957.85	$n = 24$
	Within		3843.844	− 29,875.59	42,009.74	$T = 123$
Covid	Overall	79.64092	197.4459	− 1918	2003	$N = 2952$
	Between		91.97647	3.772358	372.9512	$n = 24$
	Within		175.7127	− 1994.709	1960.877	$T = 123$

there is strong correlation driving the behavior of the variables.

These dynamics are also observed in Africa and North American countries. Generally, there is evidence that the correlation between the stock prices and number of reported cases is strongly and that increases in the number of reported cases are observed to yield lower and reduced stock prices across these countries. The findings observed during the preliminary analysis motivate the use of a panel threshold model to examine the oil–stock nexus as the threshold model captures the structural break in the relationship among variables and is popular for modeling nonlinearities in time series (see Tong 1983; Rousseau and Wachtel 2009; Girma (2005).

Models' estimation results

In this subsection, we report the estimation of the models specified in the “Empirical model” section. Basically, we use several competing models within the class of panel nonlinear models. Our reference model, as highlighted in the “Empirical model” section, is the Hansen 1999 panel dynamic threshold (PDT, henceforth) model. However, we also estimate and report additional panel nonlinear models that either accommodate threshold variable(s) or specification that allows for structural breaks (and parameter instability) in the estimates of the model's parameters. For example, we follow Seo and Shin (2016) and estimate *dynamic panel model, which allow threshold and endogeneity* in which the threshold parameter is estimated by grid search by minimizing the objective function of the generalized method of moments. In a slightly different algorithm developed by Kremer et al. (2013), we report the estimate of another *dynamic panel data threshold effects model with endogenous regressors* in which case the threshold is determined endogenously.

Our reference model, the Hansen 1999 fixed effect panel dynamic threshold model, is estimated by setting the number of thresholds to be 1 (*thnum* (1)), the number grid point search

as 400 (*grid* (400)),⁴ and the number of bootstrap replications as 300 (*bs* (300)). The number of trimming proportions is set to 1 as it must be equal to the number of thresholds specified in the “*thnum*” and the trimming proportion is set to 0.10 (*trim* (0.10)). The regime-dependent variables in the model are “oil and Cases”⁵ (*rx* (*oil Cases*)), while the threshold variable is assumed to be “oil”⁶ (*qx* (*oil*)). We use lag of oil price, (*lagoil*), lag of exchange rate (*lagexr*), and the lag of stock return (*lagstock*) as the list of regressors for regime-independent variables, while stock return (*stock*) is used as the dependent variable.

We report the estimates of the threshold in Table 3, which provides the value of the threshold parameter as 32.2500, while the lower and upper estimates of the confidence intervals are, respectively, 31.0200 and 32.7300. *Th-1* denotes the estimator in single-threshold models.

Estimates from Table 4 suggest that the null of linear model is strongly rejected, as the size of the *F* statistic is large with the probability value less than 5%. Thus, it can be inferred that our data supports nonlinearity and that there are significant threshold effects. This suggests that oil prices exhibit abrupt behavior with the emergence of COVID-19 pandemic.

Furthermore, from Table 5, we can infer the statistical significance of the regime-independent variables (*lagstock*, *lagoil*, *lager*, and *covid*) and regime-dependent regressors (*oil* and *Cases*). Except *covid* that is not too different from zero to warrant the rejection of the null hypothesis of statistically insignificance, all other variables (regime-dependent and

⁴ The grid point fixed at 300 ensures that the computational burden of the model is minimized so that we can avoid consuming time when computing large samples.

⁵ The choice of “oil and Cases” as regime-dependent variables is based on the empirical evidences that have strongly indicated that these variables are nonlinear, and they are characterized with structural breaks in their data generating process. We used unit root test such as the augmented Dickey–Fuller test and Phillips–Perron (PP) test. Due to space considerations, the results have not been presented.

⁶ The choice of oil as a threshold variable is based on empirical evidence that produces that oil prices can be used as threshold variables due to its nonlinear effects.

Fig. 1 Conditional correlation between stock prices and cases (Europe)

Fig. 2 Conditional correlation between stock prices and cases (Latin America)

regime-independent) are found to be statistically significant with the lowest probability values. Parameters of interest are the regime-dependent regressors (*oil and Cases*), which assume discrete and abrupt change with indicator function defined over the range of two values (0, 1).

We observe that the regime-dependent variables are highly statistically significant across the two regimes, with estimated coefficients that are different across the two regimes. It is imperative to note that, in our research, we define first regime (*regime_1*) as the period in which global tension due to COVID-19 pandemic is in its peak, while second regime (*regime_2*) is defined as the period with less global tension in the fear of COVID-19 pandemic. For oil prices, as one of the regime-dependent variables, the partial elasticity coefficient in the first regime is estimated to be approximately 156.93 and this partial elasticity coefficient has increased to 177.34 in the second regime. Interpreted differently, stock returns

depressed by approximately 13% between the two regimes, implying that oil price changes have negatively affected the stock returns. Equally, for cases, as the second regime-dependent variable, we observe that the more turbulent period has threshold effect which is estimated to be approximately -0.5718718 (-57.18%) and this value has reduced to approximately -0.044387 (-0.44%) in the calm period of the crisis. This implies that the value of the stock returns falls as high as 99.23% when the global economy transition from calm period of the crisis (*regime_2*) to the turbulent period of the crisis (*regime_1*). Therefore, we can infer that the threshold effects of *cases* on stock returns is statistically significant and we can interpret it to be that for a unit increase in the number of cases, stock returns deteriorate by almost 57% during the turbulent period of the crisis, while for a unit increase in the number of cases, stock returns deteriorate as low as 0.44% during the calm period of the crisis.

Fig. 3 Conditional correlation between stock prices and cases (Asia)

Table 3 Threshold estimates (level = 95)

Model	Threshold	Lower	Upper
Th-1	32.2500	31.0200	32.7300

Table 6 presents the diagnostic of the estimated model; we can say that the test statistics supporting our reference model provides overwhelming evidence that our data support the Hansen 1999 model. The within variation of the model (0.2890) is comparatively larger than between variation of the model (0.0398) as well as the overall variation of the model (0.0148). The joint influence of all the regressors is far from being irrelevant for accounting the behavior of the stock returns as the F statistics produce evidence of 168.24 test statistic with zero probability value. The unobserved component of the model is also found to be significant with the F statistic value as high as 6287.69.

With single-threshold model estimates presented in Tables 3, 4, 5, and 6, which clearly rejects the linear model, for robustness, it is natural to fit a double-threshold model. The model set up is described as the number of thresholds to be 2 ($thnum$ (2)), the number grid point search increased to 10,000 ($grid$ (10000)), and the number of bootstrap replications is set to be 1000 each (bs (1000 1000)). The number of trimming proportions is set to 2 and the trimming proportion is set to 0.05 each ($trim$ (0.05 0.05)).

Increasing the number of thresholds to 2, ($thnum$ (2)), as reported in Table 7, leaves the results somewhat similar to the estimates of single threshold. We observe that the single-

threshold estimates, $Th-1$ (or sometimes, $Th-21$) is 32.2500, while the double-threshold estimates, $Th-22$, is 52.5200. However, to search for the evidence of whether our data support double-threshold model, we report the threshold effect tests in Table 8.

In the single-threshold model, the formal hypothesis test has in its null form (H_0) that linear model is more appropriate, while the alternative hypothesis (H_a) says that single-threshold model is more appropriate. In the double-threshold model, the null hypothesis (H_0) supports the single-threshold model while the alternative hypothesis (H_a) assumes the double-threshold model. Apparently, from Table 8, we can say that our data seems to provide overwhelming evidence in support of a single-threshold model, as the size F statistics is reasonably large (245.33) with probability value less than 5%. Thus, we can say that we reject the double-threshold model with high probability value.

It is also revealing, in terms of statistical model evaluation, to compare the fixed effects regression with different number of settings by varying the number of grid point search ($grid$), the number of bootstrap replications (bs), and the number of trimming proportions ($trim$).

There are four different model version of Hansen specification, which are differed by grid search points, number of bootstrap replication, and the trimming proportion. This will help in assessing the performance of the model under different statistical setting.

Model 1, model 2, and model 3, as reported in Table 9, are all estimated with single-threshold while model 4 is estimated with double-threshold. Quantitatively, the single-threshold

Table 4 Threshold effect test (bootstrap = 300)

Threshold	RSS	MSE	F stat	Prob	Crit10	Crit5	Crit1
Single	3.88e+07	1.38e+07	254.33	0.0467	174.2263	243.5818	353.5036

Table 5 Fixed effects regression of the Hansen 1999 panel dynamic threshold model

Stock	Coeff.	Std. Err.	t	P > t	Lower CI	Upper CI
<i>lagstock</i>	54.43241	21.76541	2.50	0.010	− 23.9876	87.7654
<i>lagoil</i>	− 82.54727	31.09973	− 2.65	0.008	− 143.5271	− 21.56743
<i>lagexr</i>	1.20746	0.3980563	3.03	0.002	0.4269574	1.987962
<i>covid</i>	0.2135379	0.4525249	0.47	0.637	− 0.6737653	1.100841
<i>_cat#c.oil</i>						
0	156.9393	33.03517	4.75	0.000	92.16453	221.7142
1	177.3461	31.22538	5.68	0.000	116.1199	238.5723
<i>_cat#c. cases</i>						
0	− 0.5718718	0.0362985	− 15.75	0.000	− 0.6430452	− 0.5006984
1	− 0.044387	0.0204852	− 2.17	0.030	− 0.0845541	− 0.0042199
<i>_cons</i>	15,611.9	446.901	34.93	0.000	14,735.63	16,488.18

Table 6 Summary statistics and scalar values from the estimated fixed effects of Hansen's panel dynamic threshold model

<i>R-sq: within</i>	0.2890
<i>Between</i>	0.0398
<i>Overall</i>	0.0148
<i>corr (u_i, xb)</i>	− 0.2736
<i>F (7, 2897)</i>	168.24
<i>Prob > F</i>	0.0000
<i>sigma_u</i>	28,760.95
<i>sigma_e</i>	3660.6363
<i>rho</i>	0.98405856
<i>F test that all u_i = 0: F (23, 2897)</i>	6287.69

models (*model 1*, *model 2*, and *model 3*) are similar (although number of grid search point, number of bootstrap replication, and trimming proportion are all different) and the statistical significance of the coefficients is qualitatively similar. Interestingly, comparing single-threshold with the double-threshold (*model 1*, *model 2*, and *model 3* vs *model 4*), we can readily infer that *model 4* is not so different from the rest of the model in terms of sign as well as statistical significance of the estimated coefficients. In addition, in the case of the double-threshold model (*model 4*), although the threshold effect test for the double-threshold model is rejected, the oil price, as one of the regime-dependent variables, is highly statistically significant.

Based on the likelihood ratio statistics, we plot the confidence interval for the LR statistics in Figs. 4 and 5 in which the dynamic of the threshold variable is depicted. Clearly, from Fig. 4, the critical values fixed at 7.35 generated from the model are found to be statistically significant at 95% confidence interval. In Fig. 5, we can see that there is hardly evidence of significant threshold parameter. This, however, has buttressed that the best model for this empirical exercise is the single-threshold model (see Appendix Figs. 11 and 12).

Additional results: competing models for panel dynamic threshold

We feel that assessing the performance of empirical models from different estimation techniques is important in empirical research, as it will help in understanding data generating

process. Therefore, we propose to fit the data with competing models that are empirically used in the literature to establish threshold in a panel setting. In the empirical literature, there are alternative econometric specifications whose algorithms are designed to detect the evidence of nonlinearities, threshold detection, and finding possible structural breaks in the panel dataset. Therefore, we fit to our dataset three competing models: Seo and Shin (2016); Kremer et al. (2013); and Berthelemy and Varoudakis (1996). It is imperative to iterate that our benchmark model is Hansen model (1999) and all the competing models (Seo and Shin (2016); Kremer et al. (2013); and Berthelemy and Varoudakis (1996)) are used here to support (or refuse) the Hansen (1999) model.

To establish the empirical evidence of threshold effects, we update our data with recent econometric models. Specifically, we fit our data with the estimator proposed by Seo and Shin (2016) and statistically evaluate how well their algorithm support our data.

Of interest to the empirical work here, from Table 10, are the two estimated parameters (*kink_slope* and *r*), which are key in explaining nonlinearities and threshold in the data. The estimated parameter (*kink_slope*) captures the sudden break in at least one of the endogenous variables entering the model. Interestingly, the estimated coefficient is highly statistically significant with the lowest probability value. Additionally, the threshold parameter (*r*), which is estimated by grid search and minimizes the objective function of the generalized method of moments, is empirically found to be statistically significant. Incidentally, except for the coefficient of lagged exchange rate (*lagexr_b*), which is not very strong in the model (as the probability value is very), the coefficients for lagged oil (*lagoil_b*) and cases (*Cases_b*) are found to be reasonably good and statistically significant in the model setup.

In a slightly different estimation technique put in by Kremer et al. (2013), we explore how their proposed algorithm detects threshold effects in our data. In their model building, threshold effects and slope coefficients, which are endogenous regressor, are estimated. From the output in Table 11, we can say that our data generation process seems to reasonably behave well with the Kremer et al. algorithm as the two most important parameters (“*below_thres_sumy*” and “*above_thres_sumy*”) are found to be statistically significant with the lowest probability values. Interrogating the estimates further, we can infer that all the endogenous regressors (*lagged stock*, *lagoil*, *covid*, *Cases*), except lag of exchange rate (*lagexr*), are statistically significant. It is important to note the quantitative marginal difference between the two threshold parameters, (41.29 for the *below_thres_sumy* and 44.66 for *above_thres_sumy*) has policy implication on the stock returns.

In our last empirical exercise, we use another different algorithm, which is developed in the same spirit as Seo and Shin (2016) and Kremer et al. (2013) as well as Hansen (1999). If there is a threshold, the algorithm finds it by using the

Table 7 Threshold estimates (level = 95)

<i>Model</i>	<i>Threshold</i>	<i>Lower</i>	<i>Upper</i>
Th-1	32.2500	31.0200	32.7300
Th-21	32.2500	31.0200	32.7300
Th-22	52.5200	52.0500	53.3900

Table 8 Threshold effect test (bootstrap = 1000 1000)

Threshold	RSS	MSE	F stat	Prob	Crit10	Crit5	Crit1
Single	3.88e+07	1.38e+07	254.33	0.0480	186.5031	248.5651	391.8205
Double	3.84e+10	1.37e+07	32.60	0.5310	109.3315	165.2290	255.2422

Table 9 Model comparison: variants of Hansen panel dynamic threshold model

	Model 1 b/se	Model 2 b/se	Model 3 b/se	Model 4 b/se
<i>lagoil</i>	− 82.547** (31.10)	− 82.547** (31.10)	− 82.547** (31.10)	− 94.576** (31.03)
<i>lagexr</i>	1.207** (0.40)	1.207** (0.40)	1.207** (0.40)	1.186** (0.40)
<i>covid</i>	0.214 (0.45)	0.214 (0.45)	0.214 (0.45)	0.330 (0.47)
<i>_cat=0 # oil</i>	156.939*** (33.04)	156.939*** (33.04)	156.939*** (33.04)	108.011** (34.03)
<i>_cat=1 # oil</i>	177.346*** (31.23)	177.346*** (31.23)	177.346*** (31.23)	145.215*** (31.59)
<i>_cat=0 # Cases</i>	− 0.572*** (0.04)	− 0.572*** (0.04)	− 0.572*** (0.04)	0.585*** (0.04)
<i>_cat=1 # Cases</i>	− 0.044* (0.02)	− 0.044* (0.02)	− 0.044* (0.02)	− 0.040 (0.02)
<i>_cat=2 # oil</i>				168.655*** (31.13)
<i>_cat=2 # Cases</i>				0.094 (0.09)
<i>Constant</i>	15,611.905*** (446.90)	15,611.905*** (446.90)	15,611.905*** (446.90)	17,049.667*** (514.71)
<i>R-sqr</i>	0.289	0.289	0.289	0.297
<i>dfres</i>	2897	2897	2897	2895
<i>BIC</i>	56392.8	56,392.8	56,392.8	56,374.

Standard errors are in parenthesis

* $p < 0.05$, ** $p < 0.01$, *** $p < 0.001$

information given by the data. If there is no break point, the algorithm will automatically reject the existence of threshold in the data. This method of finding thresholds appears to be more reasonable in cases where the researcher does not know a priori the breaking point, while the theory of algorithm is

suggested in the study of Berthelemy and Varoudakis (1996). Habitually, in most empirical exercise, which is intended to establish the presence of structural break and threshold in the data, we split the sample of study in two subsamples using an exogenous break point. Most empirical researchers heavily

Fig. 4 LR statistics of the first threshold

Fig. 5 LR statistics of the second threshold **Table 10** Seo and Shin (2016) Dynamic panel data model allowing threshold and endogeneity (regression)

<i>Stock</i>	<i>Coef.</i>	<i>Std. Err.</i>	<i>z</i>	<i>P > z </i>	<i>[95% conf. interval]</i>	
<i>lagoil_b</i>	19.13311	0.9838462	19.45	0.000	17.2048	21.06141
<i>lagexr_b</i>	− 0.9834433	1.101021	− 0.89	0.372	− 3.141404	1.174518
<i>Cases_b</i>	0.0165369	0.0007968	20.75	0.000	0.0149752	0.0180986
<i>kink_slope</i>	0.9885062	0.0133115	74.26	0.000	0.962416	1.014596
<i>r</i>	9271.214	195.8322	47.34	0.000	8887.389	9655.038

Table 11 Kremer et al. (2013) dynamic panel data threshold effects with endogenous regressors

<i>Stock</i>	<i>Coef.</i>	<i>Std. Err.</i>	<i>z</i>	<i>P > z </i>	<i>[95% conf. interval]</i>	
<i>LI.</i>	0.9727953	0.0044434	218.93	0.000	0.9640864	0.9815042
<i>below_thres_sumy</i>	41.29037	7.818069	5.28	0.000	25.96724	56.61351
<i>above_thres_sumy</i>	44.66165	7.691627	5.81	0.000	29.58634	59.73697
<i>lagoil</i>	− 43.26587	7.569383	− 5.72	0.000	− 58.10159	− 28.43015
<i>lagexr</i>	0.0057066	0.1100238	0.05	0.959	− 0.2099362	0.2213494
<i>covid</i>	0.2298501	0.1098578	2.09	0.036	0.0145327	0.4451675
<i>Cases</i>	0.0114707	0.0049851	2.30	0.021	0.0017002	0.0212413
<i>_cons</i>	489.9239	118.2567	4.14	0.000	258.1449	721.7028

criticize this. Thus, in order to allow the data to speak for itself, we opt for Berthelemy and Varoudakis (1996) proposed algorithms, which find the break point endogenously.

The estimates revealed from Table 12 clearly shows that there is indeed significant break in the oil price series. The chow test, which endogenously searches and tests the significance of the break, has revealed threshold value in oil price. This test split the data into two and estimates the regression

between the two data points. From the regression tables in the appendix, however, it is worthy to mention that the estimates of the marginal coefficients differ across the two regressions. For example, from the estimates of the *regression below the threshold*, the partial coefficients of *cases* are estimated to be 0.06%. However, this coefficient is observed to have changed to 0.10% in the *regression above the threshold*.

In summary, the three additional results, Seo and Shin (2016), Kremer et al. (2013), and Berthelemy and Varoudakis (1996), which are all alternative models for estimating panel threshold effects, serve as competing models to the Hansen (1999) proposed panel threshold model. Our analysis confirms that there is presence of threshold effects among the variables considered. For example, the choice of threshold variable in Hansen (1999) is exogenously fixed, and there is readily available test statistic to decide on that the Seo and

Table 12 Berthelemy and Varoudakis (1996) break point test

<i>Break point = 4/9/2020</i>
<i>Max. QL Stat. = − 61,492.46</i>
<i>Value of oil = 20.24</i>
<i>Chow test F (5, 2918) = 0.8623932</i>
<i>P value > F = 0.4944378</i>

Table 13 Slope homogeneity test of Pesaran and Yagamata (2008)

<i>Statistics</i>	<i>P value</i>
7.738	0.000
Adj. 7.974	0.000

Shin (2016), Kremer et al. (2013), and Berthelemy and Varoudakis (1996) estimate the threshold variable endogenously.

Diagnostic tests and sensitivity analysis

It is natural to check the robustness of the proposed models and evaluate how good our estimates are in relations to various form of diagnostic available for testing the goodness of fit of the models. Therefore, we propose to test for the equality of slope coefficients among the regressors. This test is in line with panel threshold model(s) as the rejection of the hypothesis of slope homogeneity provides evidence of nonlinearities (and possible threshold) in the information sets used in the model's estimation.

From the estimates presented in Table 13, we can strongly reject the null of slope homogeneity and assume that we have strong statistical evidence that the coefficients of the variables used in the model's estimation are characterized with varying degrees of influence on the dependent variable. Based on the results in Table 13, it must be emphasized that at least one of the variables in the model is highly nonlinear and, therefore,

justify our modeling approach, which is the panel threshold model.

Equally, to buttress the nonlinearities and structural break in our dataset, and for the empirical support of panel nonlinear model, we report, as one of the diagnostics, the nonparametric estimator to simulate time-varying coefficients. This test helps to display the time-varying coefficients as they evolve smoothly overtime.

Evidently, from Figs. 6 and 7, we follow Degui et al. (2011) and fit our data with nonparametric estimator for time-varying coefficients panel data with fixed effects. We estimate and display the coefficients as they vary overtime so that evidence of parameter change can further be assessed. Figures 6 and 7 are evidences that there are parameter changes in oil prices and the number of reported cases of the pandemic. The evolution of the parameter instability provides empirical support for all the variants of threshold models fitted in our research.

In the last empirical exercise of model and data diagnostic, we run the Breusch–Pagan LM test of independence and modified Wald test for groupwise heteroskedasticity in fixed effect regression model which is presented in Table 14. We can strongly reject the null serially independent errors for the Breusch–Pagan LM test.

This implies that the data indicates cross-sectional dependence in terms of shocks among the sampled countries used in the study. In the groupwise heteroskedasticity test in fixed effect, the null of equal variance among block of countries is

Fig. 6 Structural coefficient of cases **Fig. 7** Structural coefficient of oil prices

Table 14 Breusch–Pagan LM test & modified Wald test for groupwise heteroskedasticity

Breusch–Pagan LM test of independence	
Chi-square (276)	2310.681
<i>P</i> value	0.0000
Groupwise heteroskedasticity in fixed effect regression model	
Chi-square (24)	8.8e+05
<i>P</i> value	0.0000

strongly rejected by the data. This suggests that heteroskedasticity in the panel data cannot be grouped into blocks. This finding confirms the earlier assumption that the dataset is characterized with structural breaks, extreme values, and jumps up and down sudden spikes.

Conclusions and areas of further research

The empirical quest for the research is rooted in establishing the reaction of stock market amid the COVID-19 pandemic shock. With the available data on the most affected countries in the world, we run alternative models on 24 countries and empirically deduce the evidence of nonlinearities and existence of threshold effects in information set consisting oil price, exchange rate, stock market prices, number of reported cases, and the number of death due to COVID-19 pandemic.

Our models rightly pick evidences of nonlinearities and threshold effects in oil prices. All the models estimated shows that stock market prices react in a regime-style way when the joint effects of oil prices, exchange rate changes, number of reported cases, and the number of death due to COVID-19 pandemic are analyzed.

For policy, we find that investors need to observe changes in the global number of reported cases and the number of death due to COVID-19 pandemic and how oil prices are evolving, as the global economy is further affected by the COVID-19 pandemic shock. However, our models' estimates are static and fixed overtime and this restriction may produce bias estimate of the response of stock prices for a unit shock from COVID-19 pandemic. Therefore, studies aim at examining the significance of evolution of stock price dynamics in relation to the increasing distortion of COVID-19 pandemic shock should incorporate time-variation in the modeling approach. It will be interesting to examine the reaction of stock market prices in the presence of large-scale modeling approach, as our models are capable of accommodating few numbers of variables. Health indicators, macroeconomic news, and macroeconomic uncertainty index, to mention but a few, are some of the important response variables that could have improved the precision of parameter estimation. Further research can be developed within the large-scale system so that error of omission can be minimized.

Appendix

Fig. 8 Conditional correlation between stock prices and cases (Africa) **Fig. 9** Conditional correlation between stock prices and cases (North America)

Fig. 10 Structural break tests: first simulation (bootstrap = 1000)

Fig. 11 Structural break tests: first simulation (bootstrap = 10,000)

Fig. 12 Structural break tests: first simulation (bootstrap = 100,000)

Availability of data and materials Not applicable

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Author contribution NB: Formal analysis, investigation, methodology
 NU: Writing—original draft and data curation
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