



COVID-19 pandemic and economic policy uncertainty regimes affect commodity market volatility

Maruf Yakubu Ahmed, Samuel Asumadu Sarkodie *

Nord University Business School (HHN). Post Box 1490, 8049 Bodø, Norway

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ABSTRACT

This paper investigates the switching effect of COVID-19 pandemic and economic policy uncertainty on commodity prices. We employ Markov regime-switching dynamic model to explore price regime dynamics of eight widely traded commodities namely oil, natural gas, corn, soybeans, silver, gold, copper, and steel. We fit two Markov switching regimes to allow parameters to respond to both low and high volatilities. The empirical evidence shows oil, natural gas, corn, soybean, silver, gold, copper, and steel returns adjust to shocks in COVID-19 outcomes and economic policy uncertainty at varying degrees—in both low volatility and high volatility regimes. In contrast, oil and natural gas do not respond to changes in COVID-19 deaths in both regimes. The findings show most commodities are responsive to historical price in terms of demand and supply in both volatility regimes. Our findings further show a high probability that commodity prices will remain in low volatility regime than in high volatility regime—owing to COVID-19-attributed market uncertainties. These findings are useful to both investors and policymakers—as precious metals and agricultural commodities show less negative response to exogenous variables. Thus, investors and portfolio managers could use precious metals, viz. Gold for short-term cover against systematic risks in the market during the period of global pandemic.

1. Introduction

The World Health Organization declared COVID-19 as global emergency in February 2020, and on March 11, declared the virus as global pandemic when it migrated to 110 countries with 118,000 reported cases (WHO, 2020). The recorded global growth for 2019 was 2.4% and was estimated to grow by 1%–2.5% in 2020 (WorldBank, 2020). However, since the outbreak of the coronavirus, the global economy and commodity market have recorded substantial downturn more than the 2008 financial crisis (Yakubu and Sarkodie, 2021). The global cumulative confirmed cases of COVID-19 as of November 29, were 64, 509, 752, 1,474,878 death cases, and 45, 204, 925 recovery cases. In the same timeline, the US recorded 13, 998, 001 confirmed cases, and 274,294 death cases (Worldometer, 2020). Interestingly, the first community infection of COVID-19 was recorded on February 26, 2020 and as of April 11, the U.S. recorded the highest death toll of 2108 in a single day surpassing Italy (JHUM, 2020). This necessitated the suspension of government activities and implementation of strict lockdown measures including social distancing, travel restrictions, stay at home, and other measures across the United States (Sarkodie and Owusu, 2020a,b). This

had a drastic impact on the world-leading economies, such as the United States, China, U.K, Germany, Canada, Japan, and France (Yakubu and Sarkodie, 2021).

The global economic shock since the outbreak of COVID-19 pandemic had a substantial impact on most commodity prices (Scheme 1) and was expected to persist at substantially lower rates throughout 2020 (WorldBank, 2020c). The global growth was estimated to marginally rise to 2.5% prior to COVID-19 outbreak in 2020, as against 2.4% recorded in 2019. However, the agreed estimates of growth in COVID-19 period suggest deep recession on a global scale (Yakubu and Sarkodie, 2021). The COVID-19 pandemic lockdown policy and travel restriction to mitigate the spread of the virus disrupted the supply chain—which indirectly stalled global economic growth. This is projected to be the deepest global recession the world has experienced in decades (WorldBank, 2020). The findings from a recent study show COVID-19 pandemic has greater effect on the financial market compared to any global health crisis in the last decades, including the Spanish Flu (Baker et al., 2020b). Evidence from COVID-19 effects on U. S financial stress revealed daily recoveries will cause a significant reduction in financial stress while daily deaths and economic

* Corresponding author.

E-mail address: asumadusarkodiesamuel@yahoo.com (S.A. Sarkodie).

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uncertainty policy will plunge the U.S. into financial distress (Alola et al., 2020). Thus, COVID-19 pandemic exposed how fragile the world financial and commodity market respond to global crises. The impact of COVID-19 on commodity market disrupted both demand and supply simultaneously—with varying impact across different commodities.

There are mixed findings regarding the impact of COVID-19 pandemic on commodity market and hedging potential of precious commodities. For example, the impact of COVID-19 pandemic on crude oil and natural gas on future energy market was investigated (Aloui et al., 2020). The hedging potential of gold against oil price and stock market risk was evaluated—confirming gold can be used for hedging against risks from crude oil and financial market during pandemic (Adekoya et al., 2020). The assessment of the relationship in changing regime environment of commodity and financial variables showed interrelationship among variables are regime-dependent—with duration probability higher for low variance state than high variance state (Bhar and Hammoudeh 2011). Evidence from time-varying parameter-based study suggests the first wave of COVID-19 strongly increased volatility of commodity returns (Adekoya et al., 2021). Investors uncertainty triggered by COVID-19 pandemic is reported to increase commodity price movement (Salisu et al., 2020).

Existing literature has made attempts to investigate the effects of COVID-19 pandemic on commodity market, however, majority of these studies are limited in scope. The limitation is due to the failure to include different commodities from agrarian, metals, and lag dependent variables to control for omitted variable bias. This may probably lead to estimation bias affecting statistical inferences. In essence, this paper examines the impact of the U.S. COVID-19 cases and economic policy uncertainty index on the commodity market. Contrary to existing studies, we contribute to the global debate on long-term pandemic effects on economic development—by assessing the impact of COVID-19 health outcomes, and economic uncertainty on several commodity prices namely oil, natural gas, soybean, corn, steel, silver, gold, and copper in the US. We adopt the Markov switching dynamic model to evaluate the regime-switching effects of COVID-19 health outcomes, and economic uncertainty policy on widely traded commodity returns. The regime-switching model is used to capture time series shift due to structural break among different regimes of commodity prices—particularly crude oil prices. We use lag dependent variable in the Markov regime-switching model to control for omitted-variable bias that may

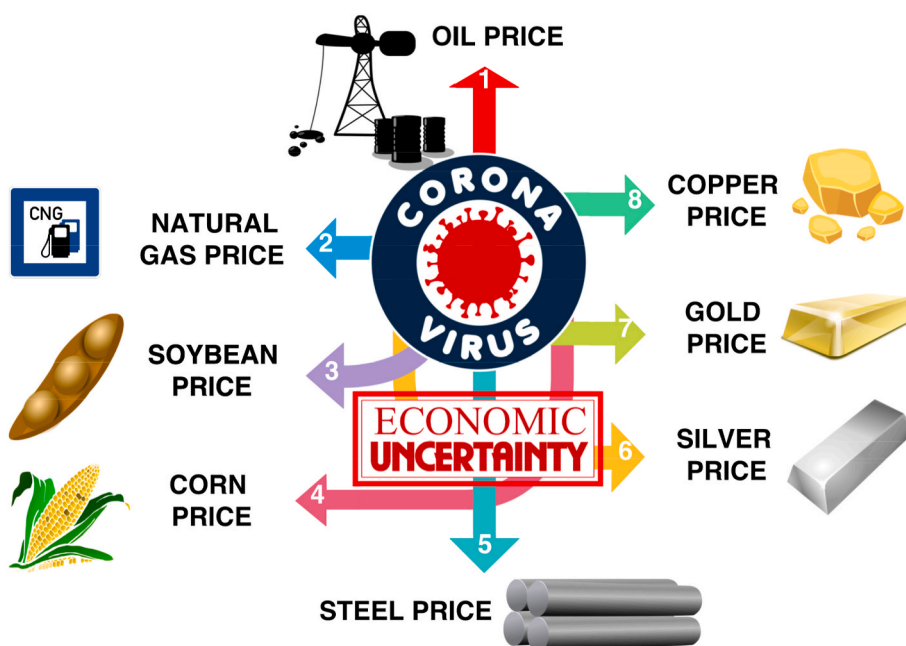
lead to estimation bias of model parameters. The Markov regime-switching dynamic approach can capture conditional volatilities at high speed. Thus, the approach has been used to capture sudden dynamic changes of behavior in crude oil price movements (Hamilton, 1989). Other studies demonstrate that using Markov switching model in examining volatilities in oil commodity-based future price series is valid (Fong and See, 2002). The Markov regime-switching model was used to study the mean shift in the U.S. gross domestic product with oil price, and estimate the transition probabilities between high and low growth regimes (Raymond and Rich, 1997).

Importantly, our empirical results will provide policymakers with relevant evidence to understand the economic implications of COVID-19 pandemic on commodity prices in different regimes. Perhaps, it will be informative to portfolio managers and investors for hedging in short-term systematic risks in their portfolio investment—particularly at times of higher uncertainty such as pandemics. Our findings may provide information that can assist investors and regulators to assess and predict transitional probabilities of commodity returns across volatility regimes.

2. Literature review

2.1. COVID-19 and commodity market

The COVID-19 pandemic has affected energy commodity prices, especially crude oil. Crude oil benchmark indexes have witnessed sharp decline — by 70% throughout the first quarter of 2020. For instance, the West Texas Intermediary (WTI) oil price fell to a negative level in the same first quarter 2020. COVID-19 lockdown measures implemented by countries such as the U.S. resulted in the collapse of transportation and travel—weakening the global demand (WorldBank, 2020a). In the first quarter of 2020, natural gas prices declined in the US by 12% and Europe by 25%. In the third quarter of 2020, the crude oil price rebound was on average 40% higher but was 30% lower than pre-pandemic level. The price rebound was driven by Organization of the Petroleum Exporting Countries (OPEC) cut in supply and eased in lockdown policies—increasing travel and transportation across the globe. The global demand for natural gas recovered, resulting in a little upward trend in price—by 18% on average in third quarter of 2020 and 3% estimation lower in 2020 relative to 2019 (WorldBank, 2020a). The agriculture



Scheme 1. Nexus between COVID-19 pandemic and commodity market prices.

commodity price on the market has been relatively stable during the pandemic. Global price of corn declined slightly in the first quarter but rose by 7% in the third quarter of 2020. The global corn production declined by 1% due to shortfall in U.S. crop harvesting. However, the global consumption of corn is estimated to grow by 2.4% in 2021 (WorldBank, 2020b). In the third quarter of 2020, soybean, and palm oil prices grew by 22% due to increase in edible oil prices. The U.S. government aided farmers and ranchers through the Corona Food Assistant Program (CFAP)—an estimated amount of 16 billion during the pandemic (USDA, 2020a). During the pre-COVID pandemic, the U.S. consumer spent ~\$137.4 billion per month on food relative to ~\$105 billion food spending in the first quarter of 2020. Total food spending in the U.S. rose in the second and third quarter of 2020 but was relatively lower compared to the same period in 2019. For instance, food spending in the U.S. was \$12 billion more in June 2019 than June 2020 (USDA, 2020).

Some studies have documented evidence of gold hedging potential and status as safe-haven asset during the COVID-19 pandemic (Conlon and McGee, 2020; Sharif et al., 2020). Notably, the impact of COVID-19 pandemic on the global economy, financial, and commodity cannot be over-emphasized. The precious metal index gained 5.4% in first quarter 2020, due to the reliance on precious metals as safe-haven commodity during the period of market uncertainties. Most investors and government were driven by gold status as a safe haven, thus, invested in gold as the price rose by 12% in the third quarter—following eight consecutive rise in price on quarterly basis (WorldBank, 2020b). The gold-based Exchange Traded Funds (ETFs) in the second quarter rose more than three-folds on yearly basis. The COVID-19 pandemic disrupted gold mining productions, restricted labor movements—particularly in South Africa, Peru, and Mexico—supporting the upward price movement in 2020 (WorldBank, 2020c). The price of silver on the commodity market dropped by 2.3% in the first quarter and rebound in third quarter when the price jumped by 50% on the market. The rise in silver price was necessitated by its lower price relative to gold price, influencing investors to purchase silver-based ETFs holding on the financial market (WorldBank, 2020b). The price of copper declined by 4.5% in the first quarter of 2020, following the higher price recorded in fourth quarter of 2019 due to the phase one China-U.S. trade deal. Global COVID-19 pandemic ignited the economic crisis, thereby affecting global industrial demand for copper. For instance, demand in China's manufacturing sector that accounts for 50% of copper consumption collapsed in the first quarter due to COVID-19 mitigating measures (WorldBank, 2020). A 22% jump in copper price in the third quarter of 2020 was driven by strong demand in China—due to strategic government stockpiling and easing of COVID-19 lockdown policy. The 2.4% gain of steel price in the first quarter of 2020 was largely due to the disruption in global supply due to COVID-19 and weather-related events including heavy rainfall and cyclones in Brazil and Australia, respectively (WorldBank, 2020c). The third quarter of 2020 saw a surge in steel price by 25%, which was largely due to strong demand in steel production in China and global supply disruption due to COVID-19—such as Brazil's Vale production hampered by labor movement and transport. However, most commodity prices recovered in the third quarter of 2020, following a steep decline in the first quarter of the year (WorldBank, 2020).

Several studies have examined the impact of health crises including COVID-19 pandemic on the global commodity and financial market. The pandemic is reported to have caused a simultaneous shock in demand and supply, affecting global trade and disrupting international supply chain (Baldwin and Tomiura, 2020). The findings show a significant influence of COVID-19 pandemic on the fragility of global economy just like the financial crisis of 2008 (Corbet et al., 2020). The COVID-19 mitigating measures that seek to curtail the spread of the outbreak cause severe economic impact across the globe. For instance, evidence from a recent study shows significant relationship between other markets and commodity market (Zhang and Broadstock, 2018). The volatility in major commodity prices has been witness simultaneously since

the pandemic. The connectedness among commodity prices has increased on average from 14.8% before the financial crisis to 47.9% thereafter the financial crisis of 2008 (Zhang and Broadstock, 2018). The COVID-19 pandemic caused a sudden decline in crude oil price and demand, resulting from restrictions in global economic activities (Rajput et al., 2020).

2.2. Economic uncertainty policy and commodity market

Investor sentiment and policy uncertainty factors play a vital role in market signals, driving commodity market (Sarkodie et al., 2021). In this scenario, potential investors and policymakers may closely monitor these factors before investing in the commodity market. Several existing literatures have explored the impact of economic policy uncertainty (EPU) on commodity market. Earlier research findings consist of studies that examine the effect of economic uncertainty on stock market returns (Pástor and Veronesi, 2013). Some findings indicate the negative effect of EPU on stock market returns, contributing to higher volatility movement in stock market (Arouri et al., 2016; Liu et al., 2017).

The bulk of literature extended the assessment into the interaction between commodity market and EPU. For instance, using linear and nonlinear Granger causality test shows evidence of causal relationship between EPU, oil, and currency market after the gold financial crisis (Albulescu et al., 2019). Findings indicate EPU has significant positive effect on metal future returns during bullish market but has significant negative effect on agriculture future returns during bearish market (Zhu et al., 2020). Similarly, movement in commodity prices is reported to predict EPU (Wang et al., 2015). The impact of EPU on international oil price occurs through spillover effect of EPU across countries including China and the US (Antonakakis et al., 2014). Besides, the relationship between EPU and commodity market is time-varying and can predict the volatility in commodity returns (Yin and Han, 2014).

In contrast, other studies reveals EPU has insignificant effect on most commodity market returns in the US (Andreasson et al., 2016; Reboredo and Uddin, 2016). Generally, the relationship between stock returns and EPU is insignificant in China and India markets (Li et al., 2016). Other existing literature suggest indirect linkage between EPU and macro-economic factors (Kim and Kung, 2017; Shahzad et al., 2017).

Other studies investigate the relationship between EPU and gold price movement on the global market. The role of gold as potential hedging mechanism was examined by incorporating the US and European EPU in short-term gold price movement. Results show growth in EPU appreciates the price of gold—making it effective tool for hedging against inflation (Jones and Sackley, 2016). The time-varying effects of country-specific EPU on precious metal price with stochastic volatility models show counterfactual shock of EPU on precious metal price changes periodically (Gao et al., 2019; Yilanci and Kilci, 2021). Thus, the casual link between EPU and precious metal price changes over the sample period.

3. Methodology

3.1. Data

We examine the impact of daily recorded cases of COVID-19 on commodity prices. The impact of the pandemic on financial and commodity market is reported to have long-term effects on sustainable economic development (Yakubu and Sarkodie, 2021). Thus, to examine the probable effect of COVID-19 cases on commodity market in the US, we retrieved data on COVID-19 outcomes from John Hopkins University and Medicine database (JHUM, 2020). The daily frequency data spans February 26, 2020–November 30, 2020, when COVID-19 cases were first reported through community spread in the US (CDC, 2020). Thus, we analyze the daily COVID-19 outcomes (confirmed, death, and recovery cases), and the US economic policy uncertainty as exogenous variables. The EPU indicator was retrieved from the U.S. Federal Reserve

Economic Data (FRED, 2020). The EPU index is based on newspapers in the United States, with further computational details expounded in Baker et al. (2020a). The endogenous variables employed include the Nasdaq indexes for gold, silver, copper, and steel—used as proxy for commodity price in the market (Nasdaq, 2020). We use the West Texas Intermediate (WTI) crude oil spot price widely recognized as commodity benchmark index for crude oil (Ahmed and Sarkodie, 2021); Henry Hub natural gas price, corn, and soybean price as extra independent variables (FRED, 2020). The commodity prices and U.S economic policy uncertainty were computed as simple first difference of natural log of daily commodity prices whereas COVID-19 outcomes entail natural log of daily compounding cases (Salisu and Adediran, 2019).

COVID-19 confirmed cases (CON), deaths (DD), and recovery cases (REC) presented in Fig. 1 show upward movement from February 26—November 30, 2020. Figs. 2–6 show volatilities in daily U.S. economic policy uncertainty index, metal commodity prices (copper and steel), precious metal commodity prices (silver and gold), agriculture commodity prices (corn and soybean), and energy commodity prices (oil and natural gas) from February 26—November 30, 2020.

3.2. Model estimation

The regime-switching model has become popular in financial modeling over the years. The first application of regime-switching involves modeling of business cycle expansion and recession to naturally capture long-term trend of economic activity cycles (Hamilton, 1989). The Markov regime-switching dynamic model captures sudden price, new dynamic prices, and fundamentals that persist after a change for several periods. The intuitive feature of regime changes in regime-switching model made the technique popular in financial modeling (Ang and Timmermann, 2012). The Markov switching model can be expressed as:

$$y_t = \beta_{st} + \pi_{1,st} y_{t-1} + \pi_{2,st} \chi_{t-1} + \theta_{st} \mu_t, \mu_t \sim iid(0, 1) \tag{1}$$

Where y_t represents the endogenous variable, which depends on the lag of endogenous variable (y_{t-1}), viz. lagged-dependent variable, χ_{t-1} denotes the lag of exogenous, st is the regime process at period t , and μ_t represents the stochastic error term. Though regime-switching could possibly influence the whole distribution, however, is somewhat limited to affect the intercept (β_{st}), autocorrelation $\pi_{1,st}$, and volatility θ_{st} of the model (Ang and Timmermann, 2012).

Our proposed model assumes the exogenous variable switch between two regimes depending on the transition probabilities of the Markov switching model from state (j) to state (i), presented as:

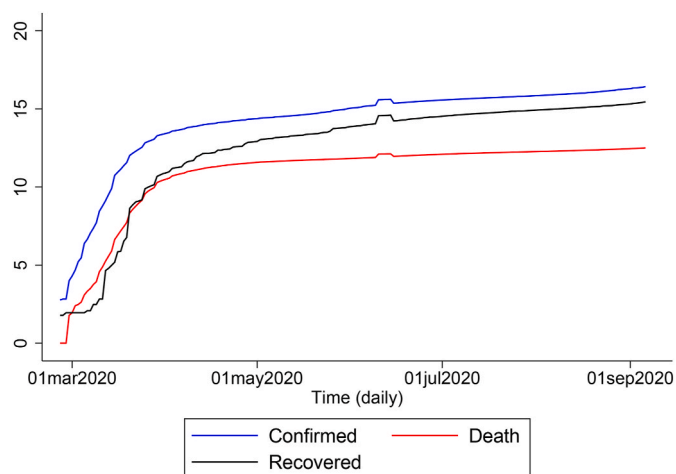


Fig. 1. The trend of COVID-19 cases in the United States.

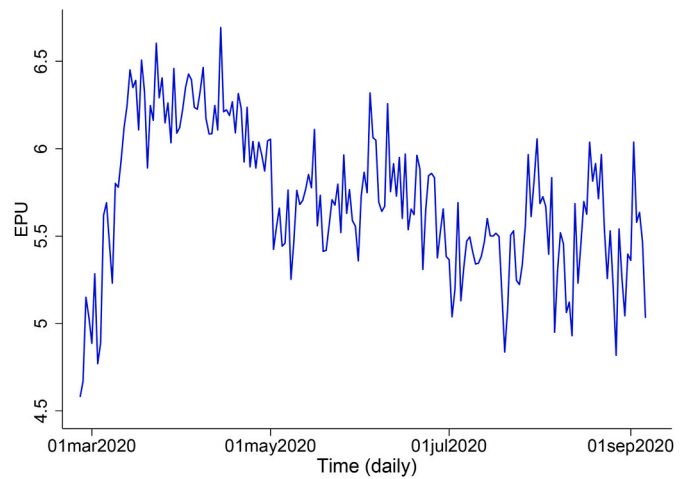


Fig. 2. The trend of US economic policy uncertainty (EPU) index.

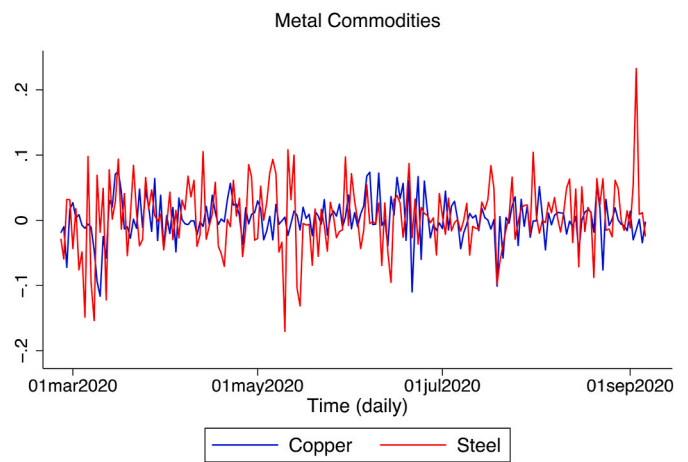


Fig. 3. Trends of metal commodity prices.

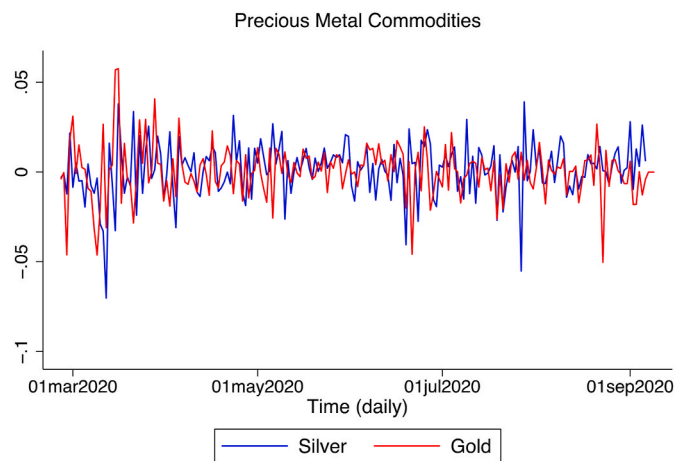


Fig. 4. Trends of precious metal commodity prices.

$$P_{ij} = \Pr(s_t = j | s_{t-1} = i), \text{ where } i = 1, 2 \text{ and } j = 1, 2. \tag{2}$$

Generally, regime transition probability could depend on time spent in the regime and time-varying Markov transition probabilities for any two-chain state achieved, where $P_{1j} + P_{2j} = 1$ for $j = 1, 2$ and $P_{1i} + P_{2i} = 1$ for $i = 1, 2$. The duration of the Markov model in regime-

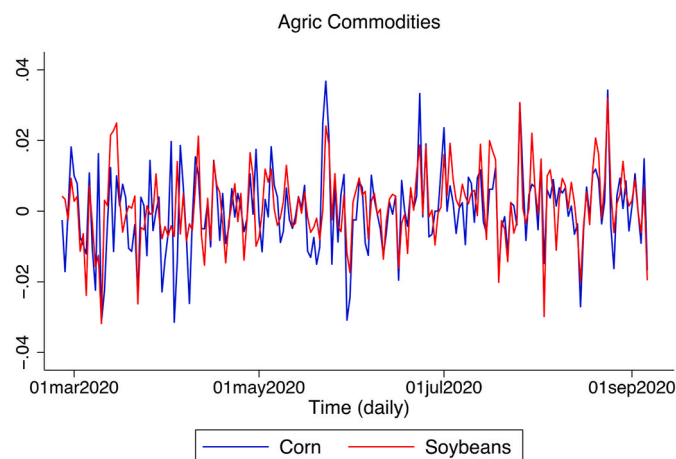


Fig. 5. Trends of agriculture commodity prices.

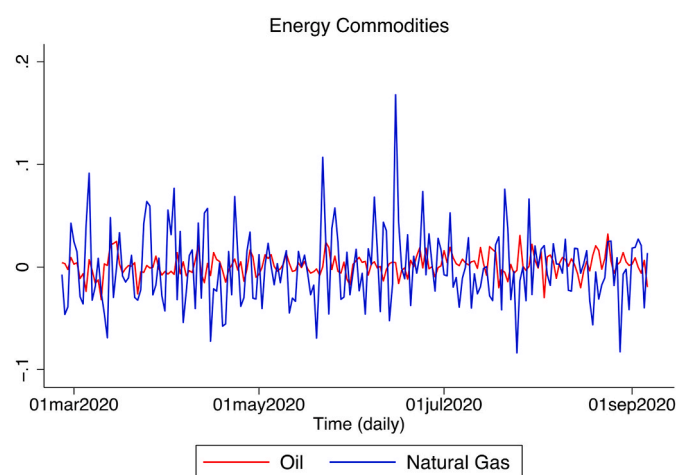


Fig. 6. Trends of energy commodity prices.

switching (i) is equal to $1/(1 - P_{ii})$. The higher the parameter P_{ii} , the higher the duration spent in regime i . The s_t is the unobserved variable of regime 1 and 2, that represents *low – price* and *high – price* commodity regimes. The details of these techniques are outlined in Hamilton (1989). For brevity, the specification of equation (1) can be expressed as:

$$\ln Y_t = \beta_{0,st} + \beta_{1,st} \ln Y_{t-1} + \beta_{2,st} \ln X_t + \mu_t \tag{3}$$

The estimated parameters include lag of oil (OIL_{t-1}), lag of natural gas (GAS_{t-1}), lag of soybean (SB_{t-1}), lag of silver (SIL_{t-1}), lag of gold (GD_{t-1}), lag of copper (COP_{t-1}), lag of steel (STL_{t-1}), oil (OIL), natural gas (NGAS), corn (CO), soybeans (SB), silver (SIL), gold (GD), copper (COP) and steel (STL). The extended version of equation (3) is presented in Appendix A.

4. Results & discussion

Prior insights about sampled data characteristics presented in Table 1 are examined using descriptive statistical analysis including mean, standard deviation, kurtosis, skewness, Jarque-Bera and correlation. The findings show SB has the highest average market price relative to COP, CO, GD, EPU in 194 days. The mean of CON, DD, and REC cases in 194 days were 4,279,915, 133,416 and 1,520,024 people, respectively. The Jarque-Bera test of the sample data series indicates the rejection of the null hypothesis of normal distribution for all series excluding GD. This implies the variables except GD fails the normality assumption. Thus, we transformed the data series to control heteroskedasticity.

4.1. Unit root test

We examine the stationarity properties of the sampled variables using Augmented Dicky-Fuller test (ADF) and Philip-Perron test (PP). This is useful to control for spurious regression, hence, producing robust estimates (Dickey and Fuller, 1981; Perron, 1989). The results of PP and ADF unit root are presented in Table 2. Evidence from both PP and ADF tests in Table 2 shows the log level of all variables confirm the rejection of the null hypothesis of unit root at 1% significance level. Thus, all sampled variables are $I(0)$ and hence, exhibit a stationary process.

Table 1
Descriptive statistical analysis.

Stats	CON	COP	CO	DD	EPU	GD	GAS	OIL	REC	SIL	SB	STL
Mean	4,279,915	2.747	12.730	133,416	329.435	1803.121	1.982	35.318	1,520,024	20.734	934.660	8.008
Median	3,457,114	2.865	12.635	137,594	296.200	1805.250	1.825	39.515	1,062,490	19.665	892.250	7.795
Maximum	13,541,185	3.440	14.390	268,045	807.660	2112.560	3.140	48.670	5,146,319	29.260	1191.750	14.550
Minimum	16	2.100	11.540	0.000	97.490	1477.300	1.330	-36.980	6	11.770	821.750	4.900
Std. Dev.	3,565,971	0.333	0.779	80,284	136.584	128.347	0.406	10.086	1,439,703	4.668	99.902	1.588
Skewness	0.577	-0.186	0.466	-0.305	0.801	-0.306	1.125	-2.603	0.621	0.028	1.075	1.429
Kurtosis	2.337	1.775	2.013	1.930	3.241	2.448	3.466	15.500	2.169	1.622	2.995	6.729
Jarque-Bera	14.333	13.245	14.886	12.261	21.230	5.478	42.675	1481.980	18.067	15.385	37.346	178.455
p-value	0.001***	0.001***	0.001***	0.002**	0.000***	0.065	0.000***	0.000***	0.000***	0.000***	0.000***	0.000***
Observations	194	194	194	194	194	194	194	194	194	194	194	194
Correlation												
CON	1											
COP	0.923	1										
CO	0.461	0.389	1									
DD	0.948	0.925	0.222	1								
EPU	-0.479	-0.656	-0.397	-0.496	1							
GD	0.761	0.825	-0.017	0.849	-0.429	1						
GAS	0.704	0.629	0.474	0.604	-0.354	0.507	1					
OIL	0.520	0.704	0.258	0.574	-0.725	0.531	0.305	1				
REC	0.996	0.916	0.516	0.930	-0.489	0.737	0.715	0.513	1			
SIL	0.800	0.880	0.157	0.848	-0.570	0.937	0.592	0.634	0.789	1		
SB	0.927	0.823	0.728	0.799	-0.475	0.546	0.667	0.442	0.944	0.625	1	
STL	0.702	0.619	0.397	0.657	-0.383	0.373	0.515	0.431	0.681	0.390	0.698	1

Note: ***, and ** denote the rejection of null hypothesis at 1% and 5% significant level.

Table 2
Unit root test.

Variable	ADF test	PP test
	Level	Level
OIL	-11.447***	-11.366***
GAS	-13.629***	-13.694***
CO	-12.927***	-12.888***
SB	-11.447***	-11.366***
SIL	-15.874***	-15.783***
GD	-13.715***	-13.714***
COP	-13.784***	-13.864***
STL	-14.374***	-14.438***
CON	-15.094***	-15.141***
DD	-12.082***	-14.687***
REC	-5.549***	-4.927***
EPU	-5.457***	-5.101***

Notes: *** denotes 1% significant rejection of the null hypothesis of the unit root test.

4.2. Energy commodity

The coefficients of Markov switching regression model for oil and natural gas commodities in two regimes are presented in Table 3. The two regimes of these commodities can be classified as low volatility and high volatility regimes. As shown in Tables 3, 1% increase in COVID-19 daily confirmed cases will provoke a decline by 0.007% in low volatility but increase by 0.013% in high volatility regime in oil returns. The daily recovery cases of COVID-19 reported a positive coefficient in low and high volatility regimes. An increase in daily recovery cases induce an increase in oil returns by 0.034% at p -value < 0.1 in high volatility

Table 3
Markov Regime Switching Results in Oil and Gas Price function.

Variable	lnOIL Coefficients		lnGAS Coefficients	
	Regime 1	Regime 2	Regime 1	Regime 2
$lnOIL_{t-1}/lnGAS_{t-1}$	-0.721*	0.208***	0.011	-0.638
Std Err	(0.433)	(0.074)	(0.074)	(0.504)
$lnCON/lnCON_{t-1}$	-0.001*	0.0001**	-0.0002	0.009***
Std Err	(0.000)	(0.000)	(0.000)	(0.002)
P_{11}	0.162	0.411	0.988	0.011
P_{22}	0.036	0.035	0.447	0.848
$lnOIL_{t-1}/lnGAS_{t-1}$	0.115	0.695	-0.175	-0.056
Std Err	(0.137)	(1.077)	(0.216)	(0.093)
$lnDD_{t-1}$	0.0001	0.0003	0.002	0.001
Std Err	(0.000)	(0.001)	(0.003)	(0.001)
Cons	-	-	0.050	-0.018
Std Err	-	-	(0.035)	(0.017)
P_{11}	0.913	0.316	0.318	0.199
P_{22}	0.452	0.829	0.055	0.063
$lnOIL_{t-1}/lnGAS_{t-1}$	0.074	0.218	0.015	-3.629**
Std Err	(0.099)	(0.149)	(0.067)	(1.293)
$lnREC_{t-1}$	0.0003	0.0003*	0.0003	-0.011*
Std Err	(0.000)	(0.000)	(0.001)	(0.006)
Cons	-	-	-0.007	0.262***
Std Err	-	-	(0.009)	(0.076)
P_{11}	0.215	0.284	0.980	0.014
P_{22}	0.170	0.443	0.000	1.00
$lnOIL_{t-1}/lnGAS_{t-1}$	0.088	0.152	-0.059	-0.190
Std Err	(0.083)	(0.248)	(0.103)	(0.253)
$lnEPU_{t-1}/lnEPU$	-0.003	0.023**	-0.001	0.011***
Std Err	(0.002)	(0.011)	(0.001)	(0.004)
Cons	0.020	-0.133	-	-
Std Err	(0.012)	(0.066)	-	-
P_{11}	0.255	0.555	0.931	0.063
P_{22}	0.030	0.031	0.211	0.693

Notes: *, **, *** represent significant level at 10%, 5% and 1%; parenthesis denotes the standard error (Std Err); P_{11} and P_{22} denote probabilities in low regime and high regime, respectively.

regime and 0.026% in low volatility regime at p -value > 0.05. The economic policy uncertainty in Table 3 reports a negative and positive coefficient in both regimes, indicating a 1% increase will cause 0.33% decline in oil returns in low volatility regime at p -value > 0.05 and 2.3% increase in oil returns in high volatility regime at p -value < 0.05. The economic policy uncertainty index is constructed based on the volatility in economic activities. The lagged oil price exhibits a negative and positive coefficient in low and high volatility regimes at p -value < 0.05. This indicates 1% increase in historical oil price will decrease oil returns by 72% in low volatility regime and increase by 21% at high volatility regime. This indicates oil returns are responsive to historical price changes and sensitive to oil supply and demand in both regimes. The collapse of oil demand resulted from COVID-19 mitigating measures and the breakdown of oil production agreement among the Organization of the Petroleum Exporting Countries (OPEC) and its partners in the third quarter of 2020 (WorldBank, 2020a). This may result in surplus which will likely exceed storage capacity and cause widespread shutdown of production plants in the US and Canada.

The negative coefficient in low volatility regime can be explained by the outgrowth in COVID-19 cases that resulted in global emergency and lockdown policies that curtailed transport and travel—which account for ~67% of oil demand, particularly in the US (WorldBank, 2020a). The high significance level of coefficients reported for high volatility regime compared to low volatility regime implies a decrease in oil return affects the probability of observing high volatility regime. Hence, investors are likely to buy more oil due to stress of high uncertainty in economic recession when oil price is low during pandemic. The COVID-19 daily deaths and historical price of oil report a positive coefficient in both regimes with statistically insignificant impact on oil commodity. The increase in COVID daily recovery cases may likely reduce the lockdown policies and travel restrictions implemented globally, thereby increasing fuel consumption for transportation and production through rebound of economic activities. The oil market witnesses a positive supply trend and negative demands due to significant transportation and economic shutdown induced by COVID-19 containment measures (Rajput et al., 2020; WorldBank, 2020).

The results from Table 3 provide evidence on the effect of COVID-19 cases on natural gas returns. An increase in COVID-19 daily confirmed cases by 1% will increase natural gas returns by 0.86% in high volatility regime, but decline by 0.016% in low volatility regime. The lagged natural gas price is statistically insignificant for both regimes—with inference in predicting the natural gas returns. This indicates historical natural gas returns are not sensitive to its fundamentals. The transition probability in low volatility regime is ~98% whereas high volatility regime is ~45%. These probabilities are different from those reported on oil commodities. The significant statistical inference of the positive coefficient of high volatility regime can be explained by COVID-19 lockdown policies in the U.S—that ensure people work from home and stay indoors, hence, increasing natural gas driven electricity consumption. Thus, given that natural gas is the primary source for electricity generation—electricity peak demand increases due to residential cooling and heating. As of 2019, natural gas contributed 43% of electricity generation in the U.S. (IEA, 2020). COVID-19 daily deaths and lagged natural gas price show positive and negative insignificant coefficients in both regimes, respectively. The coefficient associated with COVID-19 daily recoveries is negative in low volatility regime at no significant level but significantly positive at high volatility. The intuition is that increasing COVID-19 daily recovery cases may induce lax lockdown policies with few people staying indoors, hence, reducing electricity demand. The lagged natural gas price reports negative and positive coefficients in both regimes with statistical significance in high volatility regime. The transition probability of low volatility regime is reported at 98% whereas high volatility regime is negligible. A 1% change in economic policy uncertainty will cause insignificant decline in natural gas returns by 0.13% but a significant 1.1% increase in natural gas returns in the latter regime. Our findings are consistent with studies suggesting

energy commodity price shows more volatility movement than metal commodity during the COVID-19 pandemic period. For instance, crude oil price shows higher negative than positive overaction during the COVID-19 pandemic period (Borgards et al., 2021).

4.3. Agriculture commodity

Despite the mix and moderate impact on agriculture commodities during the COVID-19 pandemic, the global and domestic supply chain disruption and restrictions on exports or stockpile commodities raise concerns about risks on food security. The Markov switching regression results on corn and soybean commodities are presented in Table 4. The results show COVID-19 confirmed, death and recovery cases record negative coefficients for low volatility regime with no statistical inference but significant positive coefficient at high volatility regime. A 1% increase in confirmed, death and recovery cases will insignificantly lead to a decline in corn returns by 0.016%, 0.018%, and 0.004% in low volatility regime. In high volatility regime, a 1% increase in confirmed, death and recovery cases will statistically increase corn returns by 0.14%, 0.144%, and 0.114%, respectively. This indicates that in stress economic uncertainty environment characterized by high volatility regime, COVID-19 confirmed, death, recovery cases, and economic policy uncertainty index have a positive relationship with corn returns due to decline in oil and natural gas production resulting from low market price. This may influence the price of crops used for biofuel production such as corn and soybeans (Rajput et al., 2020). The insignificant results reported for low volatility regime may be due to low sensitivity to external shocks that are not fundamentals to crops including corn during pandemic (WorldBank, 2020b). This perhaps implies most agrarian commodities serve as a necessity for global food security. Table 4 shows economic policy uncertainty has significant

Table 4
Markov Regime Switching Results in Corn and Soybean Price function.

Variable	lnCON Coefficients		lnSB Coefficients	
	Regime 1	Regime 2	Regime 1	Regime 2
$\ln CO_{t-1} / \ln SB_{t-1}$	–	–	–0.721*	0.208*
Std Err	–	–	(0.433)	(0.000)
$\ln CON_{t-1} / \ln CON$	–0.0002	0.001**	–0.0007*	0.0001**
Std Err	(0.001)	(0.001)	(0.000)	(0.000)
Cons	0.006	–0.024**	–	–
Std Err	(0.009)	(0.010)	–	–
P_{11}	0.513	0.276	0.162	0.411
P_{22}	0.288	0.464	0.036	0.035
$\ln DD_{t-1}$	–0.0002	0.001**	–0.0004	0.003**
Std Err	(0.001)	(0.001)	(0.001)	(0.001)
Cons	0.006	–0.019***	0.005	–0.026**
Std Err	(0.007)	(0.008)	(0.005)	0.012
P_{11}	0.514	0.276	0.790	0.122
P_{22}	0.282	0.476	0.370	0.328
$\ln CO_{t-1} / \ln SB_{t-1}$	–	–	0.077	0.213
Std Err	–	–	(0.101)	(0.148)
$\ln REC_{t-1}$	–0.00004	0.001**	0.0003	0.0004*
Std Err	(0.001)	(0.001)	(0.000)	(0.000)
Cons	0.004	–0.018***	–	–
Std Err	(0.008)	(0.009)	–	–
P_{11}	0.550	0.342	0.209	0.290
P_{22}	0.337	0.531	0.170	0.440
$\ln CO_{t-1} / \ln SB_{t-1}$	–	–	–0.617	0.208**
Std Err	–	–	(0.580)	(0.089)
$\ln EPU_{t-1}$	–0.004***	0.0002	–0.003	0.0003***
Std Err	(0.001)	(0.000)	(0.002)	(0.000)
P_{11}	0.274	0.209	0.255	0.555
P_{22}	0.043	0.043	0.031	0.030

Notes: *, **, *** represent significant level at 10%, 5% and 1%; parenthesis denotes the standard error (Std Err); P_{11} and P_{22} denote probabilities in low regime and high regime, respectively.

negative impact on corn returns in low volatility—however, high volatility regime is characterized by uncertainty that may affect the economy. The transitory probabilities of low and high volatility regimes are reported as 27% and 4.3%, respectively.

From Table 4, COVID-19 cases of confirmed, death, recovery, and economic policy uncertainty index have significant positive relationship with soybean returns in high volatility regime but negative in low volatility regime. Agricultural commodities have a stable price during the pandemic, hence, characterized by low volatility regime in normal economic state. In contrast, COVID-19 deaths, recovery cases, and economic policy uncertainty do not influence soybean returns. Perhaps, low sensitivity of agrarian commodities such as soybeans to market shocks is not critical to commodity dynamics. However, the positive significant coefficient in high volatility may be due to the decline in production of crude oil and natural gas—influencing the use of biofuel from soybeans and hoarding behavior by consumers during the early stages of the lockdown. Higher transition probabilities are reported for low volatility regimes than higher volatility regimes. Our empirical findings corroborate studies indicating slowdown of economic activities due to global COVID-19 mitigating policies affecting energy demand, and metal commodities compared to demand for agriculture commodities (Baffes et al., 2020).

4.4. Precious metal commodity

We observe a significant negative and positive coefficient for both low and high volatility regimes in Table 5. This indicates that 1% increase in COVID-19 cases in confirmed, death and economic policy uncertainty will trigger 0.026%, 0.033%, and 0.06% increase in silver

Table 5
Markov Regime Switching Results in Silver and Gold Price function.

Variable	lnSIL Coefficients		lnGD Coefficient	
	Regime 1	Regime 2	Regime 1	Regime 2
$\ln SIL_{t-1} / \ln GD_{t-1}$	0.782***	–0.231***	–0.128*	0.993***
Std Err	(0.292)	(0.061)	(0.069)	(0.219)
$\ln CON$	–0.003***	0.0003***	–0.001*	0.003***
Std Err	(0.000)	(0.000)	(0.000)	(0.001)
Cons	–	–	0.010*	–0.042***
Std Err	–	–	(0.006)	(0.013)
P_{11}	0.292	0.194	0.934	0.041
P_{22}	0.019	0.029	0.180	0.816
$\ln SIL_{t-1} / \ln GD_{t-1}$	0.925***	–0.233***	–0.127*	1.013***
Std Err	(0.274)	(0.061)	(0.069)	(0.219)
$\ln DD$	–0.004***	0.0003***	–0.001	0.003**
Std Err	(0.001)	(0.000)	(0.000)	(0.001)
Cons	–	–	0.006	–0.032***
Std Err	–	–	(0.005)	(0.010)
P_{11}	0.320	0.213	0.936	0.040
P_{22}	0.018	0.026	0.181	0.819
$\ln SIL_{t-1} / \ln GD_{t-1}$	–0.233***	1.129***	–0.130*	1.056***
Std Err	(0.062)	(0.267)	(0.069)	(0.223)
$\ln rREC / \ln REC_{t-1}$	0.0003***	–0.004***	–0.001	0.002*
Std Err	(0.000)	(0.001)	0.000	0.001
Cons	–	–	0.007*	–0.025***
Std Err	–	–	(0.004)	(0.010)
P_{11}	0.976	0.237	0.935	0.041
P_{22}	0.017	0.662	0.190	0.814
$\ln SIL_{t-1} / \ln GD_{t-1}$	0.308	–0.223***	–0.148**	0.525***
Std Err	(0.356)	(0.062)	(0.069)	(0.189)
$\ln EPU$	–0.006***	0.001***	0.001	0.060***
Std Err	(0.001)	(0.000)	(0.003)	(0.015)
Cons	–	–	–0.003	–0.351***
Std Err	–	–	(0.015)	(0.086)
P_{11}	0.258	0.186	0.940	0.044
P_{22}	0.021	0.030	0.177	0.710

Notes: *, **, *** represent significant level at 10%, 5% and 1%; parenthesis denotes the standard error (Std Err); P_{11} and P_{22} denote probabilities in low regime and high regime, respectively.

returns in high volatility regime. In the same high volatility regime, a 1% increase in COVID-19 recovery cases declines silver returns by 0.37% at p -value < 0.01 . The low volatility regime reports -0.29% , -0.4% , -0.62% , and 0.028% coefficients for confirmed cases, deaths, economic policy uncertainty, and recovery cases, respectively. A change in COVID-19 confirmed, death cases will reduce silver returns whereas a change in COVID-19 recovery cases will increase silver returns. In both volatility regimes, silver returns are responsive to historical prices and likely to influence future prices. The transitional probability is high in low volatility regime than high volatility regime. This indicates high probability of the Markov switching model for silver returns staying in the first regime than the second regime. COVID-19 confirmed cases, death cases, and economic policy uncertainty have a significant negative relationship with silver returns than gold returns. This indicates silver and gold do not respond positively to COVID-19 pandemic cases and economic policy uncertainty index in low volatility regime, even though their price on commodity market has been fairly stable compared to other metal commodities (WorldBank, 2020). An increase in COVID-19 confirmed and death cases will result in more aggressive lockdown policies and travel restrictions by the US—thereby negatively affecting the price of silver on the market. In contrast, an increase in COVID-19 recovery rates may lead to flexible lockdown policies, thereby affecting the price of silver positively. However, in high volatility regime, the Markov switching model has low probability of transition to silver—inferring silver can serve as safe-haven during the global pandemic, but less strong than gold. The low price of silver relative to gold price during COVID-19 pandemic also enticed investors to invest in silver-backed Exchange Traded Fund (ETF) holdings, almost doubling the previous record in 2009 financial crisis (WorldBank, 2020).

The results from the Markov-Switching model in Table 5 show a positive significant coefficient in the higher volatility regime. A 1% change in the COVID-19 cases of confirmed, death, recovery, and economic policy uncertainty index will provoke a change of 0.282%, 0.276%, 0.16%, and 6.03%, respectively, in high volatility regime. The COVID-19 confirmed cases report a significant negative coefficient whereas deaths, recoveries, and economic policy uncertainty index have no statistical significance. Gold returns have historical growth in both regimes. This indicates gold is responsive to historical supply and demand in both low and high volatility. Power outages or labor unrest in South Africa and political conflicts in Sub-Sahara Africa and Middle East affected gold prices without affecting the macroeconomic factors on consistent basis. Besides, demand for jewelry and official buyers fell by about 50% (WorldBank, 2020). It can be observed that gold serves as a haven in high volatility regime with strong statistical inference ranging from 1% for confirmed cases and economic policy uncertainty index, 5% for death cases, and 10% for recovery cases. Our results suggest gold acts as safe-haven during pandemic whereas demand for gold ETFs rose rapidly above three-fold year-on-year in the second quarter of 2020 on the financial market. Therefore, gold performs better in the high volatility regime than silver. This finding contradicts other studies that investigate the safe-haven characteristic of gold, and silver—suggesting silver is stronger safe-haven commodity than gold against a fall in stock market (Lucey and Li, 2015). The results from the low volatility regime can be due to COVID-19 confirmed cases that led to strict lockdown policies affecting the economy. This negatively affects the price of gold on the commodity market. The results from the Markov switching model indicate gold returns have high probability of staying in the first volatility than the second volatility regime. The rise in gold price reflects investor uncertainty in the market, however, gold is a stronger hedge commodity in global financial crises or risks, especially when gold market is performing and trading at higher prices (Boubaker et al., 2020). Our findings are consistent with studies that suggest crisis tend to negatively affect gold price, but to lesser extent, compared to similar safe-haven precious metal (Huang and Kilic, 2019). These findings are consistent evidence suggesting the hedging potential of gold during pandemics for seeking short-term cover and diversification of market

risks (Adekoya et al., 2021). Additionally, the degree of gold hedging potential is time-varying and evidence from this study corroborate previous studies that find gold as hedging tool against macroeconomic indicators (Adekoya et al., 2021; Baur and McDermott, 2010). Our findings are in line with studies showing evidence of existing relationship between uncertainty and precious metal price movement (Gao et al., 2019; Huynh, 2020; Yilanci and Kilci, 2021). On the contrary, the findings suggest the inability of gold to hedge certain commodities such as oil against market shock like the COVID-19 pandemic (Salisu and Adediran, 2020).

4.5. Metal commodity

The Markov switching model results from Table 6 for copper returns reveal that COVID-19 cases of confirmed, deaths, recoveries, and economic policy uncertainty index have no statistical implication on copper returns in low volatility regime. The high volatility regime reports a statistically significant response for copper returns. A 1% increase in COVID-19 cases of confirmed, deaths, recoveries, and economic policy uncertainty spur copper returns by 0.53%, 0.41%, 0.82%, and 1.77%, respectively in high volatility regime. Unlike gold and silver returns that reported a significant response to the exogenous variables, copper returns report insignificant response in low volatility regime. This may be due to a price jump in copper price by 22% in the third quarter of 2020 — the highest change recorded since the second quarter of 2019. This was driven by the surging import and demand from China, as restriction on COVID-19 were eased and stimulus package took effect (WorldBank, 2020b). Although copper returns exhibited less significant positive response to all exogenous variables, it is not likely to serve as a

Table 6
Markov Regime Switching Results in Copper and Steel Price function.

Variable	lnCOP Coefficients		lnSTL Coefficients	
	State1	State2	State1	State2
$\ln COP_{t-1} / \ln STL_{t-1}$	-0.228***	0.901***	-0.187***	1.943***
Std Err	(0.078)	(0.217)	(0.067)	(0.353)
$\ln CON$	0.001	0.005*	0.001**	0.002
Std Err	(0.001)	(0.003)	(0.000)	(0.001)
Cons	-0.009	-0.066*	-	-
Std Err	(0.014)	(0.038)	-	-
P_{11}	0.942	0.038	0.902	0.047
P_{22}	0.188	0.457	0.000	1.000
$\ln COP_{t-1} / \ln STL_{t-1}$	-0.229***	0.931***	-	-
Std Err	(0.079)	(0.213)	-	-
$\ln DD$	0.001	0.004*	-0.002	0.008***
Std Err	(0.001)	(0.003)	(0.002)	(0.003)
Cons	-0.009	-0.036*	0.036	-0.095***
Std Err	(0.012)	(0.024)	(0.023)	(0.027)
P_{11}	0.945	0.037	0.241	0.204
P_{22}	0.187	0.438	0.841	0.185
$\ln COP_{t-1} / \ln STL_{t-1}$	-	-	-0.1881***	1.897***
Std Err	-	-	(0.068)	(0.343)
$\ln REC$	-0.001	0.008*	0.001**	0.002
Std Err	(0.001)	(0.005)	(0.000)	(0.002)
Cons	0.008	-0.094***	-	-
Std Err	(0.011)	(0.031)	-	-
P_{11}	0.953	0.069	0.901	0.048
P_{22}	0.305	0.416	0.000	1.000
$\ln COP_{t-1} / \ln STL_{t-1}$	0.266	0.059	-0.185***	1.961***
Std Err	(0.184)	(0.122)	(0.067)	(0.376)
$\ln EPU$	0.001	0.018***	0.001*	0.003
Std Err	(0.010)	(0.007)	(0.001)	(0.003)
Cons	-0.024	-0.087**	-	-
Std Err	(0.055)	(0.041)	-	-
P_{11}	0.045	0.064	0.901	0.046
P_{22}	0.205	0.712	0.000	1.000

Notes: *, **, *** represent significant level at 10%, 5% and 1%; parenthesis denotes the standard error (Std Err); P_{11} and P_{22} denote probabilities in low regime and high regime, respectively.

safe-haven commodity for investors due to copper’s strong linkage to real economy of the US and global economy (Bhar and Hammoudeh, 2011). The lagged copper return has significant negative and positive relationship with copper returns in low and high volatility regimes. This indicates copper returns respond to historical changes including pandemic-induced supply disruptions from COVID-19 rising cases that resulted in temporary suspension of operations at Coldeco state-owned company in Chile—the largest copper producer in the world (World-Bank, 2020b). The Markov switching model shows high probability of remaining in low volatility regime than high volatility regime, consistent with other results reported herein.

The steel Markov switching model results presented in Table 6 reveal a 1% change in COVID-19 confirmed, recovery cases and economic policy uncertainty will stimulate steel returns by 0.048%, 0.052%, and 0.12% in low volatility regime. In the high volatility regime, there is no significant relationship between steel returns and COVID-19 cases of confirmed, recovery, and economic policy uncertainty, but COVID-19 deaths report significant relationship with steel returns. The significant positive coefficient reported in low volatility regimes may be due to robust demand in steel production in China—leading to 25% increase in price in the third quarter of 2020—when COVID-19 restrictions were eased due to low reported cases (WorldBank, 2020). Steel returns have significant relationship with its lagged returns in both regimes. This indicates that steel returns are influenced by historical demand and supply. A typical example is the disruption of production at Brazil’s Vale due to lack of transport and labor resulting from COVID-19 outbreak and tougher supervisory requirement and implementation following the Brumadinho dam collapse in the first quarter of 2019 (WorldBank, 2020b). These Markov switching model equations for steel report high probability of staying in low volatility regimes than in high volatility regimes. Our findings are aligned with studies that show cumulative impulse response of gold return is more stable compared to other metal commodities such as copper, silver, and aluminum in the height of COVID-19 pandemic (Ezeaku et al., 2021).

4.6. Model verification

To validate the estimated models, we incorporated lagged-dependent variables to control for potential omitted-variable bias. Second, we adopted several diagnostic tests to examine the residual independence of the estimated models. Table 7 provides evidence of the post estimation diagnostics after analyzing and discussing the findings of the Markov-Switching models. The results show evidence from Breusch-Godfrey test, Durbin Watson test, heteroskedasticity, skewness, and kurtosis. The majority of the estimated models herein show evidence of no serial correlation, autocorrelation, heteroskedasticity. Few models examined in this study show evidence of heteroskedasticity, however, without compromising the structural stability of model residuals (see Fig. 7). To control this, we carried out the CUSUM structural test—to ascertain the parameter stability of the data series with its residuals (Fig. 7). The plots of cumulative sum of square emanate from equations 4-35 (see Appendix A) based on the regression with corresponding 95% confidence bands generated from the CUSUM square test. The underlying principle of the CUSUM structural test is that any movement outside the 95% confidence bands shows structural instability of the model. Evidence from our estimated CUSUM tests in Fig. 7 reveals the plots are within the 95% confidence band across all models, hence, confirming the long-term stability of the estimated models.

5. Conclusion

In this paper, we examined the dynamic relationship between commodity prices, COVID-19 health outcomes, and economic policy uncertainty in the US using Markov regime-switching estimation technique. The underlining Markov switching regimes used in this study can be interpreted as low volatility and high volatility regimes. The

Table 7
Model Validation using diagnostic test.

	Breusch-Godfrey	Durbin-Watson	Heteroskedasticity	Skewness	Kurtosis
InOIL					
Equation 4	0.799	1.966	0.813	0.707	0.041
Equation 5	0.765	1.966	0.709	0.673	0.041
Equation 6	0.659	1.962	0.588	0.849	0.040
Equation 7	0.670	1.965	0.516	0.875	0.027
InGAS					
Equation 8	0.100	1.989	0.970	0.265	0.298
Equation 9	0.103	1.989	0.983	0.266	0.298
Equation 10	0.156	1.989	0.971	0.263	0.297
Equation 11	0.792	1.991	0.795	0.291	0.306
InCO					
Equation 12	0.512	1.889	0.282	0.441	0.024
Equation 13	0.513	1.889	0.325	0.443	0.024
Equation 14	0.584	1.909	0.380	0.328	0.027
Equation 15	0.442	1.863	0.992	0.261	0.026
InSB					
Equation 16	0.765	1.965	0.807	0.723	0.041
Equation 17	0.128	1.662	0.292	0.374	0.020
Equation 18	0.726	1.964	0.577	0.865	0.039
Equation 19	0.670	1.965	0.516	0.875	0.027
InSIL					
Equation 20	0.780	1.991	0.001**	0.028	0.163
Equation 21	0.890	1.993	0.001**	0.024	0.155
Equation 22	0.971	1.997	0.002**	0.032	0.153
Equation 23	0.455	1.984	0.023**	0.026	0.197
InGD					
Equation 24	0.791	2.001	0.000**	0.016	0.007
Equation 25	0.960	1.999	0.000**	0.014	0.008
Equation 26	0.749	2.001	0.000**	0.008	0.006
Equation 27	0.234	2.016	0.021**	0.002	0.005
InCOP					
Equation 28	0.230	1.993	0.004**	0.063	0.017
Equation 29	0.855	2.026	0.045**	0.061	0.017
Equation 30	0.896	2.018	0.084	0.077	0.015
Equation 31	0.467	2.012	0.017**	0.020	0.033
InSTL					
Equation 32	0.695	2.002	0.102	0.108	0.146
Equation 33	0.412	2.116	0.140	0.286	0.156
Equation 34	0.751	2.000	0.098	0.107	0.148
Equation 35	0.539	2.006	0.538	0.150	0.127

Notes: ** denotes the rejection of the null hypothesis at 5% significance level. The model specification of equations 4-35 is presented in Appendix A.

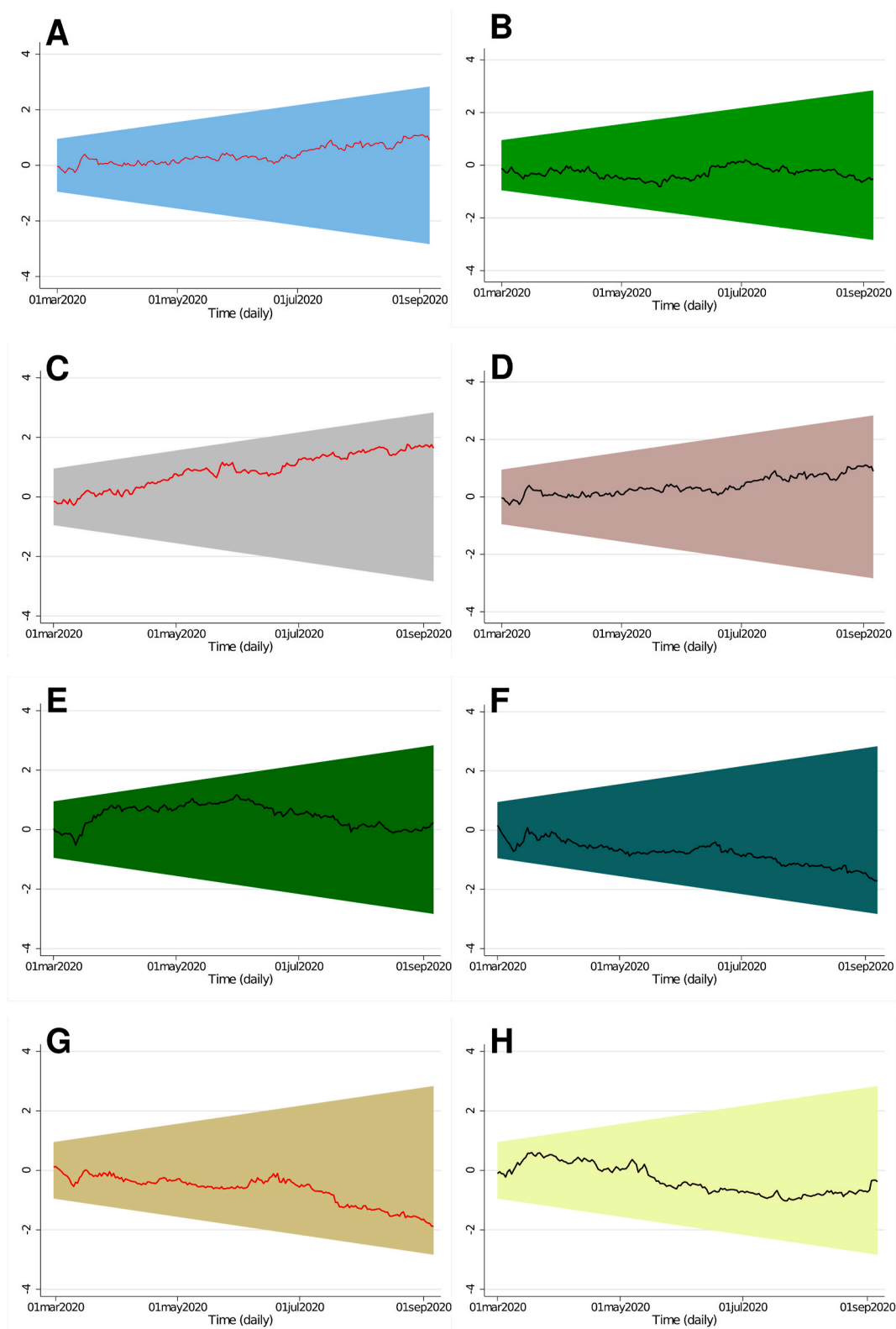


Fig. 7. CUSUM stability test of (A) Model 4 (B) Model 8 (C) Model 12 (D) Model 16 (E) Model 20 (F) Model 24 (G) Model 29 (H) Model 32. The specification of models 4-32 is presented in Appendix A.

COVID-19 pandemic has increased uncertainty in the general economic activities, affecting the performance of global financial and commodity markets. The commodities used in this study include oil, natural gas, corn, soybeans, silver, gold, copper, and steel and economic policy uncertainty policy as the exogenous variable. In all our Markov switching

models, the relationship between the variables provides evidence of regime dependence—and the expected probability transition is much higher in low volatility regimes than high volatility regimes. Evidence from these findings implies most commodity prices are likely to have more waiting periods in low volatility regimes than in high volatility

regimes. This infers economic development during pandemics is more likely to stay in low regime than in high regime. These findings are therefore relevant to investors, portfolio managers, and policymakers.

In our oil-based Markov model, high COVID-19 confirmed cases is problematic for oil price commodity due to COVID-19 mitigating measures that drastically curtailed travel and transport—accounting for ~67% of oil demand in low volatility regimes. High COVID-19 cases affect the price of natural gas demand, but the impact is much smaller given the primary use of natural gas for electricity generation and residential heating and cooling due to COVID-19 policies on movement restrictions. In contrast, high COVID-19 recovery cases will reduce natural gas returns due to lax lockdown policies.

The relationship between corn returns, soybean returns to the COVID-19 confirmed, death, recovery cases, and economic policy uncertainty index is positive in high volatility regime. In low volatility regime, corn returns report insignificant relationship due to the low sensitivity of agrarian commodities to external shocks. Evidence from the study indicates soybean returns are responsive to historical growth in demand and supply of soybeans in both regimes.

We report positive and significant relationship of silver and gold returns to the COVID-19 cases and economic policy uncertainty index in high volatility regime. Silver and gold returns are responsive to historical market demand and supply in both regimes. In the low volatility regime, gold return is less responsive to the COVID-19 cases and economic policy uncertainty index due to its safe-haven potential. Unlike gold return, silver return is more responsive to COVID-19 cases and economic policy uncertainty due to its weak safe-haven advantage compared to gold.

Evidence from copper-based and steel-based Markov switching model reveal both commodities are sensitive to historical market growth and thus, likely to predict future market trends in both volatility regimes. Both the price of copper and steel grew by 22% and 25% following a robust demand and surge in imports in China during the third quarter of 2020. The positive significant response of copper to COVID-19 health outcomes and economic policy uncertainty in high volatility regime can be associated with rising prices and fall in supply of copper in the market.

These findings can provide insight into the hedging potential of gold and silver during pandemics. Gold and silver hedging potential are time-varying and regime dependent, implying that they vary across Markov regimes. Investors can effectively hedge in short-term against systematic risks in portfolio investment. Future potential investors can be guided by the outcome of our empirical findings for similar future pandemics. The results can also assist regulators to assess and predict the probability of the market staying in one regime and initiate new economic adjustment to a new normal. The findings from oil and natural gas return can assist oil-exporting countries in formalizing policies against future global pandemics on energy commodity prices on the world market. Given that most commodities are responsive to historical market trends, policymakers like OPEC could curtail supply to boost demand. Future studies can utilize sophisticated models such as dynamic autoregressive distributed lag to test the impact of counterfactual shocks across commodity markets.

Author contributions

M.Y.A: Conceptualization; Data curation; Writing - original draft; Software; Validation; Writing - original draft. S.A.S: Conceptualization; Funding acquisition; Software; Validation; 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.

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Appendix A. Supplementary data

Supplementary data to this article can be found online at <https://doi.org/10.1016/j.resourpol.2021.102303>.

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