Commodity spot prices and the US stock market performance: evidence from the COVID-19 crisis

Journal of Derivatives and Quantitative Studies: 선물연구

313

Received 21 February 2025
Revised 12 July 2025
1 August 2025
Accepted 3 September 2025

Quazi Nur Alam
Department of Finance, American International University- Bangladesh, Dhaka, Bangladesh, and
Dipta Banik
Department of Finance, Muma College of Business, University of South Florida, Tampa, Florida, USA

Abstract
We examine whether the US stock market significantly responds to the movement of commodity spot prices during the COVID-19 crisis. We regard gold and crude oil as representatives of the commodity spot market, movements in the S&P 500 index as a proxy to the US stock market performance and movements in sector-specific weekly market capitalization as the sector performance. Our empirical findings show that the movement of the S&P 500 index is significantly associated with fluctuations in gold prices but not in crude oil prices during the Covid-19 crisis. However, the 2SLS regression results show a significant comovement between commodity spot prices and the index, the results consistent with the potential omitted variable bias issues in our original regression analysis. The incremental effect of gold (crude oil) price on the index movement was dominant in the post-lockdown (pre-lockdown) period. During the COVID-19 crisis, both gold and crude oil prices had a unidirectional negative effect on the performance of specific sectors such as healthcare and energy. Only crude oil prices have a significantly negative effect on the performance of consumer discretionary, IT and utility sectors, whereas only gold prices significantly negatively impacted the performance of others such as industrial, materials, real estate, financial and communication services sectors. Uniquely, gold prices positively influence the performance of the consumer staples sector during the crisis. Our findings are robust with the instrumental variable approach and immune to simultaneity bias. Our study is the first to explore the association between commodity spot prices and the US stock market performance during the COVID-19 crisis while controlling for the effects of market and economic factors.

Keywords US Economy and Stock Market, US stock market in COVID-19 crisis, commodity spot price movement and US stock market, Fed's policy interventions in the COVID-19 crisis
Paper type Research article

1. Introduction

COVID-19 shook the US economy with a rapid surge of positive cases all over the country. In March–June 2020, the US government introduced nonpharmaceutical policy interventions (NPI) such as travel bans, mandatory closure of schools, strict social distancing requirements, stoppage of international trade, etc. (Spiegel and Tookes, 2021). In fear of potential threats from restrictions surrounding the crisis to their stock investments, the investors embarked on a selling spree, causing a tumble in the S&P 500 index (Chan *et al*., 2021). However, with the COVID-19 vaccination beginning to be offered in December 2020, the US stock market rebounded quickly: the S&P 500 index gained 21.0% from Jan 2021 to Mar 2022.

JEL Classification — G10, G11

Journal of Derivatives and Quantitative Studies: 선물연구
Vol. 33 No. 4, 2025
pp. 313-332
Emerald Publishing Limited
e-ISSN: 2713-6647
p-ISSN: 1229-988X
DOI 10.1108/JDQS-02-2025-0007

In this paper, we empirically examine whether the commodity spot market influences the performance of the US stock market during the COVID-19 crisis. Existing literature finds a close connection between the performance of the commodity futures market and the US stock market (Nguyen *et al*., 2020; Liu and Guo, 2022; Wen and Wang, 2021; Mensi *et al*., 2021; Kang *et al*., 2024). However, these studies do not control the effect of market and economic factors.

The rationale behind the choice of our research question is that small retail trades dominated large trades during the COVID-19 crisis (Clancey-Shang, 2023; Sigalas, 2023); retail traders were actively engaged in both momentum and contrarian trading strategies and their activity was associated with weaker market quality near the onset of the crisis (Pagano *et al*., 2021). Since retail investors and small institutions are often more reactive to short-term news and price movements than large institutional investors, who tend to focus on long-term fundamentals, it is reasonable to expect that fluctuations in commodity spot prices significantly influenced their stock investment decisions during the COVID-19 crisis.

The existing literature shows a direct connection between the COVID-19 crisis and the US stock market performance and empirically presents how systematic risks led by business restrictions or NPI during the crisis affect stock prices (e.g. Erdem (2020) and Rizwan *et al*. (2020)). However, existing studies have not empirically examined the relationship between the commodity spot market and the US stock market performance after controlling for the movements of market and economic factors.

The wavelet coherence analysis of Managi *et al*. (2021) shows that crude oil futures prices countercyclically affect the US stock market. Their study projects that the COVID-19 crisis tagged with the oil price shock can negatively affect the US stock market. Although their study finds a high degree of comovement between oil prices and the US stock market, it fails to consider other contributory factors to the stock market performance. However, the quantitative model set forth by Kilian and Park (2009) presents that the jump in the oil price led by economic expansions has persistent positive effects on the stock market. Their model findings suggest that the demand and supply shocks in crude oil futures account for nearly 22% of the long-run variance of cumulative real returns of the US stocks. Similarly, we observe that the movements of crude oil spot prices from publicly available data somewhat resemble the movement of the S&P 500 index. Both crude oil spot prices and the S&P 500 index started declining during Jan 2020–Mar 2020 and then regained positive momentum in the forwarding periods during the crisis. Besides, we observe high volatility in gold spot prices during the crisis period. Arfaoui and Rejeb (2017) also finds that the volatility in gold futures prices temporarily exaggerates the downfall of the US stock market performance during any crisis. Existing literature documents a strong comovement between commodity futures prices and stock prices. However, as Pindyck (2001) emphasizes, both spot and futures prices are determined by the equilibrium conditions in the cash market for spot sales and the inventory market. Besides, Li and Chavas (2022) finds a positive contemporaneous codependence between futures price and spot price. Given the well-established comovement between commodity futures and spot prices, as well as between futures prices and stock returns, it is reasonable to expect a meaningful degree of correlation between commodity spot prices and US equity returns—particularly during periods of heightened market stress such as the COVID-19 crisis. While this relationship is reasonable, our use of spot prices across the commodities is a deliberate modeling choice aimed at ensuring consistency and capturing actual transaction values. Second, using spot prices allows us to maintain comparability across commodities and better reflect the realized prices that economic agents face. Third, unlike commodity futures, physical commodities are directly traded in markets, and their demand largely depends on the purchasing power of consumers and businesses. Rising spot prices of commodities can, at least to some extent, reduce the investable amount and investment scope for retail investors and smaller institutional investors. Even if these investors do not buy commodities directly, the broader economic effects of higher commodity prices—such as increased living or production costs—may lead to greater uncertainty and concern about lower investment returns, especially among retail investors. We do not claim the use of spot prices as a methodological innovation, but rather as a practical and economically meaningful choice.

Hence, we develop our only null hypothesis –

H1. The commodity spot market does not have a significant effect on the US stock market performance during the COVID-19 crisis.

The remainder of the paper is organized as follows. Section 2 introduces the data. In this section, we show sample selection and variable construction. Section 3 presents the empirical analysis. Section 4 concludes.

2. Data

2.1 Sample selection

We choose a sample period from January 2020 to March 2022 since COVID-19 was prevalent in the US during that time. We collect daily S&P 500 index data, daily share price data, and the total number of shares outstanding (NOS) of all S&P 500 stocks from Yahoo Finance for the sample period. From NASDAQ, we collect data for Gold Spot prices and Crude Oil Spot (the OPEC Reference Basket [1]) prices for the sample period. We use the data of the Bureau of Economic Analysis (BEA) to get macroeconomic news announcements. We use the daily data of Federal Reserve Economic Data (FRED) to gather the percentage changes in job postings on Indeed, Fed Funds effective rate, federal reserve balance (in USD trillion), 10-year breakeven inflation rate, nominal broad US dollar index, and six-month treasury bill rate. We also use the Bloomberg Database to gather credit default swap (CDS) rate and 6-month LIBOR rate for the sample period. We extract COVID-19-related news from FRASER (owned by the Federal Reserve Bank of St. Louis).

2.2 Variable construction

2.2.1 S&P 500 index. The study by Blume and Edelen (2004) finds that the market value of the S&P 500 index represents 68.7% of the market value of all traded equities in the US. This benchmark index regularly drops and adds companies based on liquidity, public float, market capitalization, and quarterly earnings. Their evidence shows that the S&P 500 index has lower tracking errors than the Russell 3,000 index and is consistent with the exact replication strategy. Following the findings of Blume and Edelen (2004), we consider the S&P 500 index a proxy for the US stock market. We collect daily index values from Jan 2020 to Mar 2022 and determine the daily market capitalization of all stocks by multiplying the number of outstanding shares with the daily price data. We also derive changes in the daily market capitalization of each sector in the S&P 500 index. Then, we resample the data into weekly observations. Sectoral returns and S&P 500 index returns are considered dependent variables in our regression. Here, we classify stocks into 11 sectors according to the Global Industry Classification Standard (GICS) by MSCI and S&P.

2.2.2 Main variables. Gold and Crude oil are two alternative assets often used to hedge the investment portfolio and are considered representatives of the commodity spot market (Coronado *et al.*, 2018; Sari *et al.*, 2010). Therefore, *Gold and Crude Oil* are two main variables of interest in our regression. *Gold* is the average weekly spot price of gold in the London Bullion Market Association (LBMA). *Crude Oil* is the weighted average weekly price of crude oil settled by OPEC member countries.

2.2.3 Control variables. We also use a set of controls (i.e. market and economic factors) that may significantly influence the US stock market performance. We follow the existing literature to choose these control variables in our regression analysis. The liquidity preference theory set forth by Keynes (1937) suggests that the rate of interest is governed by the supply and demand for credit and that the banking system can influence the rate of interest through its ability to disburse credit. Chen *et al.* (1986) corroborate the effects of the term structure of interest rates on demand and supply for credit and provide empirical evidence that the unanticipated change in the term structure significantly influences stock returns. Therefore, we use the *6-mo T-Bill Rate*, which is the real interest rate for the 6-month treasury bill, to control the effect of the supply and demand for credit on stock performance.

During the Covid-19 crisis, the existing literature provides somewhat pessimistic forecasts for major macroeconomic and other variables (e.g. Primiceri and Tambalotti (2020) and Ng (2021)), investors also suspect the negative sentiment of both the US economy and the stock market during the crisis. Envisioning the plausible negative reaction to the stock market investments, the federal reserve made necessary policy interventions to increase fund flows and boost investors' confidence, as found by Cachanosky *et al.* (2021). As the Fed cut its short-term rates in Mar 2020 and started buying treasury securities and disbursing loans to banks, there was an upsurge (67%) in the federal reserve balance during Mar 2020–May 2020 and then a gradual increase in the balance in forwarding periods. To control the effect of the Quantitative Easing initiative by the Federal Reserve, we include *FRB*, which is the total assets of the Federal Reserve (in trillion USD), in our regression model. The total assets of the FRB include treasuries, mortgage-backed securities, and federal agency debt.

Our choice of controls is motivated by the liquidity preference theory as we find that the Fed reduced the short-term rates to increase the demand for credit by potential investors during the COVID-19 crisis. The Federal Reserve cut the Fed funds rate from 1.59% in Mar 2020 to 0.05% in Apr (2020) and the 6-month treasury bill rate from 1.52% in Feb 2020 to 0.14% in Apr (2020) to increase the money supply and revive positive momentum in the stock market. As conceptualized by Quan (2022), the quantitative easing policy of the Fed initially led to an upsurge in stock prices during the crisis. He suggests that the interest rate policy of the central bank during the COVID-19 crisis boosts the capital market in four ways such as demand and supply effects, income effects, expectation effects, and cost effects. However, he does not provide any empirical evidence for his findings relevant to the relationship between the Fed interest policy and the US stock market performance. Contrary to the conceptualized assessment of Quan (2022), our assessment is mostly empirical. To control the effects of the credit market liquidity conditions on stock performance, we employ in our regression *Fed Funds Rate*, which is the short-term interest rate at which depository institutions lend reserve balances to other depository institutions overnight on an uncollateralized basis. We also employ in our regression model *CDS Spread*, which is the difference between the 6-month CDS rate in the US and the 6-month LIBOR, to control the effects of credit risk on stock performance during the Covid-19 crisis.

The empirical model set forth by Cornell (1982) shows that money supply announcements by the Fed lead to a rise in inflation or an increase in real interest rate in anticipation of future tightening monetary policy. Contrary to Keynesian predictions, his model findings show a positive correlation between money supply innovations and the US Dollar performance. We also observe a similar incidence when the Fed undertook the quantitative easing programs and cut the short-term interest rates. The performance of the US Dollar against European currencies peaked (up 26%) during Jan–Mar 2020 and then started declining till the end of 2020 while we observe the opposite for the breakeven inflation rate during that period. Therefore, to control the effects of ex-ante supply-side shocks (i.e. food and oil price fluctuations) on stock performance, we employ in our regression model *BEI*, which is the market's projected average inflation rate over the next 10 years, calculated by comparing the yield of a 10-year Treasury bond to the yield of a 10-year Treasury Inflation-Protected Security (TIPS).

We also observe that the S&P 500 index moved in the opposite direction of the nominal broad US dollar index. Our findings are justified by the proposition of Sujit and Kumar (2011): the USD exchange rate has a historically negative correlation with the S&P 500 index movement. Contrary to this finding, Malik (2021) finds little connection between the USD exchange rate and volatility transmissions across the stock market. Motivated by these conflicting findings, we employ in our regression model the nominal broad US dollar index (NBUDI) to control the effects of the exchange rate fluctuations on stock performance.

There is vast literature that shows evidence of the strong relationship between the job market conditions and stock performance. Mortensen and Pissarides (1994) proposes the aggregate unemployment model, which suggests that the cyclicality of unemployment increases with the short-run response of job destruction to endogenous shocks. Moreover, the model set forth by Tortorice (2013) provides empirical evidence in support of the aggregate unemployment model that endogenous separation and wage rigidity explain 75% of the observed variance of US unemployment. Our selection of controls is also motivated by the aggregate unemployment model since the COVID-19 crisis, an endogenous shock to the US economy, caused a sudden increase in the unemployment rate from Jan 2020 to Mar 2020.

Though the US unemployment rate declined from its highest record (14.7%) in Apr (2020) to 6.7% in Dec 2020, as shown by Bianchi *et al.* (2021), that rate in the first half of the crisis period remained comparable to that of other endogenous shocks (10% during the 2007–09 great recession and 10.4% during the post-World War II period). There is a consensus, as outlined in Feldmann (2011) and Hall (2017), that fear of economic recessions reduces employers' investment in job creation and overall fund flows to the stock market. Therefore, we employ in our model *Job Postings*, which is a negative percentage change in job postings in Indeed and a proxy for temporary unemployment shock, to control the effect of the US employment conditions on stock performance during the crisis.

As summarized in Boudon (2003), the rational choice theory postulates that people make choices that help them achieve their objectives, given all relevant factors beyond their control. However, the assumptions of this theory are directly criticized when panic distorts rational investment choices. As presented in the empirical research of Lai and Roy (2005), the S&P 500 index tumbles with any significantly negative macro news announcements since such announcements often create panic among investors. Nevertheless, the study by Rangel (2011) finds that daily macro news announcements have little effect on stock market jump intensity dynamics. These conflicting findings motivate us to employ in our regression model the *Macro News Effect*, which is the net negative effect of macroeconomic news in the stock market.

As Baker *et al.* (2020) show, the US stock market volatility in March 2020 surpassed the historical market volatility records observed in December 2008, October 1987, late 1929, and the early 1930s. The massive volatility at the onset of the COVID-19 crisis in the United States can be compared with that during the Spanish Flu of 1912, Swine Flu, MERS, SARS, etc. The existing literature shows that the news of crisis events such as the 2007–08 financial crisis, the Black Monday in 1987, the Great Crash of 1929, etc. had similar confluence with the large daily market volatility observed during the COVID-19 crisis (e.g. Mazur *et al.* (2021), Jebabli *et al.* (2022), Moschonas (2020)). Therefore, we employ in our regression model *COVID News Effect*, which is the net negative effect of COVID-related news in the stock market. Besides, we also employ in our regression model *Election Effect* is an indicator variable that takes 1 after the last US national election and 0 otherwise. We include this variable in our regression to control the effects of the US election on the US stock market performance during the crisis. For our regression, we resample data in weekly observations and use indexing for all variables.

3. Empirical analysis

3.1 Summary of descriptive statistics

Table 1 presents findings from descriptive statistics for the sample period (Jan 2020–Mar 2022). During that period, the S&P 500 index gained on average 17.4% with a standard deviation of 19.0%, skewness of −0.278, and kurtosis of −1.0. Therefore, the movement of the index was random and symmetric. All sectors except the Energy sector gained on average during this period. Gold price increased on average by ~18.0% while the Crude Oil price declined on average by ~10.0% during the sample period.

Table 1. Summary statistics

Variables	Obs	Mean	5th Pctl	25th Pctl	Median	75th Pctl	95th Pctl	Std Dev	Kurtosis	Skewness
Health Care	118	0.196	−0.046	0.037	0.178	0.377	0.445	0.174	−1.145	−0.046
Industrials	118	0.110	−0.252	−0.040	0.122	0.288	0.333	0.192	−0.913	−0.559
Consumer Discretionary	118	0.478	−0.071	0.236	0.589	0.713	0.927	0.320	−0.766	−0.546
Information Technology	118	0.439	−0.058	0.176	0.459	0.706	0.901	0.309	−1.022	−0.175
Consumer Staples	118	0.117	−0.069	0.028	0.112	0.198	0.308	0.115	−0.778	−0.125
Utilities	118	0.040	−0.107	−0.025	0.047	0.101	0.181	0.087	−0.273	−0.225
Financials	118	0.062	−0.312	−0.195	0.064	0.288	0.379	0.241	−1.417	−0.196
Materials	118	0.223	−0.182	0.029	0.276	0.421	0.506	0.229	−1.036	−0.430
Real Estate	118	0.109	−0.139	−0.031	0.051	0.286	0.382	0.175	−1.245	0.173
Energy	118	−0.153	−0.484	−0.352	−0.123	−0.016	0.283	0.232	−0.111	0.487
Communication Services	118	0.264	−0.104	0.060	0.286	0.472	0.563	0.224	−1.102	−0.219
S&P500 Index	118	0.174	−0.146	0.020	0.188	0.343	0.443	0.190	−1.014	−0.278
Gold	118	0.178	0.027	0.140	0.180	0.226	0.283	0.071	0.225	−0.534
Crude Oil	118	−0.100	−0.666	−0.351	−0.060	0.097	0.428	0.327	0.091	0.178
CDS Spread	118	0.667	−0.211	0.026	0.265	0.770	3.338	1.084	6.518	2.407
6-mo T-bill rate	118	0.174	0.026	0.039	0.072	0.118	0.994	0.266	4.403	2.355
NBUDI	118	0.004	−0.033	−0.017	0.000	0.015	0.075	0.029	0.789	1.087
BEI	118	0.115	−0.406	−0.078	0.222	0.339	0.500	0.287	−0.697	−0.478
FRB	118	0.770	0.000	0.680	0.797	1.002	1.135	0.313	1.106	−1.243
Fed Funds Rate	118	0.141	0.032	0.052	0.052	0.058	1.000	0.266	6.537	2.862
Job Postings	118	0.134	−0.364	−0.085	0.033	0.412	0.607	0.312	−1.226	0.135
Macro news effect	118	0.153	−2.000	0.000	0.000	1.000	2.000	1.137	1.682	−0.305
Covid news effect	118	0.720	−1.000	0.000	1.000	1.000	3.000	1.246	1.001	0.360
Election effect	118	0.627	0.000	0.000	1.000	1.000	1.000	0.486	−1.746	−0.533

Source(s): Authors' work

3.2 Model estimation

Table 2 presents the correlation-coefficient matrix that helps us decide which variables show moderate-to-severe multicollinearity. From our observation of Table 2, we decide to exclude any control variable in our regression model that shows a severe correlation with the main variables of interest (i.e. Gold and Crude Oil). Besides, we estimate VIF scores (i.e. regressing the variables of interest on a set of control variables) and exclude some control variables from each regression model with a VIF score at or above 10 by following Thompson *et al.* (2017). We are flexible in setting the benchmark VIF (i.e. 10) because it is reasonable to expect some level of correlation between commodity prices and market and economic factors. For brevity, we do not report the VIF results.

White (1980) presents a covariance matrix estimator that results in consistent parameter estimates (though not the most efficient) in the presence of heteroskedasticity. We detected heteroskedasticity in our initial OLS estimates; as a result, our standard errors and t-statistic values were inconsistent. We use the Heteroskedasticity Consistent Covariance Matrix (HCC) proposed by White (1980) to obtain consistent parameter estimates.

3.3 Baseline results

This section presents the regression results that assess the influence of the commodity spot market on the overall US stock market performance. For 118 observations (From Jan 2020 to Mar 2022), we design a time-series regression to assess the effect of commodity prices on the S&P 500 index performance and sector-specific returns. Addressing the multicollinearity issues, we use 3 models for each of the main variables of interest: Gold and Crude oil. The control variables used in these models are CDS Spread, Six-month Treasury Bill Rate, NBUDI, BEI, FRB, Fed Funds Rate, Macro news effect, COVID news effect, and Election effect.

We prioritize Model 2 for Gold and Model 5 for Crude Oil because they control for the marginal effect of the Federal Reserve's quantitative easing (QE) initiatives on US stock market performance. Our economic rationale is that QE policies moderate the underlying relationship between commodity prices and equity returns. Specifically, QE programs—characterized by large-scale asset purchases and near-zero interest rates—exerted a substantial influence on stock prices during the COVID-19 crisis. By design, low interest rates increase investor appetite for riskier assets such as equities, while asset purchases directly boost stock market performance through enhanced liquidity and market support. Consequently, we focus our interpretation on Models 2 and 5, which better isolate the effect of commodity price movements net of monetary policy interventions. Nevertheless, we report results from the other models as well, since they provide insight into how stock market responses to commodity prices might have unfolded in the absence of large-scale monetary stimulus.

In Model 2 of Table 3, we observe that the US stock market performance is significantly negatively associated with the gold spot price (significant at 1% level) when we control for the effect of the quantitative easing initiative by the federal reserve along with other controls. The result in Model 2 suggests that ceteris paribus, a one-standard-deviation increase in the gold spot price is associated with an average decrease in the S&P 500 Index of 2.1% relative to its sample mean. Our result is consistent with Callahan (2002), who finds a negative correlation between a firm's exposure to gold futures prices and its stock performance. However, we do not find a significant relationship between the crude oil price and the S&P 500 index. For brevity, we avoid analyzing the relationship between the US stock market performance and control variables.

In Table 4, we regress sector-specific performance during the COVID-19 crisis on commodity prices. Here, the model numbering is consistent with that in Table 3. Each panel in Table 4 represents the regression result for each sector.

We find that the performance of the Healthcare sector is significantly negatively associated with commodity spot prices. We observe that the quantitative easing initiative by the federal

Table 2. Correlation coefficient matrix for regression variables

Pearson correlation coefficients, $N = 118$
p-values are in parenthesis

	CDS spread	Six-month treasury bill rate	Gold futures	NBUDI	BEI	FRB	Crude oil Futures	Fed funds rate	Job postings	Covid news effect	Macro news effect
CDS Spread	1										
Six-month Treasury Bill Rate	−0.171	1									
	(0.065)										
Gold	−0.062	−0.440	1								
	(0.505)	(<0.0001)									
NBUDI	0.273	0.122	−0.361	1							
	(0.003)	(0.188)	(<0.0001)								
BEI	0.044	−0.075	0.389	−0.726	1						
	(0.638)	(0.422)	(<0.0001)	(<0.0001)							
FRB	0.180	−0.569	0.626	−0.386	0.731	1					
	(0.051)	(<0.0001)	(<0.0001)	(<0.0001)	(<0.0001)						
Crude Oil	0.048	0.218	0.252	−0.554	0.907	0.582	1				
	(0.607)	(0.018)	(0.006)	(<0.0001)	(<0.0001)	(<0.0001)					
Fed Funds Rate	−0.157	0.899	−0.600	0.066	−0.216	−0.770	0.013	1			
	(0.089)	(<0.0001)	(<0.0001)	(0.477)	0.019)	(<0.0001)	(0.893)				
Job Postings	0.161	0.026	0.199	−0.500	0.890	0.661	0.912	−0.117	1		
	(0.082)	(0.779)	(0.030)	(<0.0001)	(<0.0001)	(<0.0001)	(<0.0001)	(0.207)			
Covid news effect	−0.030	−0.318	0.097	0.204	−0.185	0.069	−0.291	−0.345	−0.283	1	
	(0.747)	(0.000)	(0.298)	(0.026)	(0.045)	(0.456)	(0.001)	(0.000)	(0.002)		
Macro news effect	−0.037	0.107	−0.140	0.011	−0.022	−0.116	0.020	0.109	0.030	0.024	1
	(0.691)	(0.251)	(0.131)	(0.902)	(0.817)	(0.210)	(0.828)	(0.240)	(0.747)	(0.794)	

Source(s): Authors' work

Table 3. US Stock market performance – shifts in the S&P 500 index

S&P 500 Index Variables	(1)	(2)	(3)	(4)	(5)	(6)
Intercept	274.77	319.64	48.52	239.35	244.30	48.32
	(4.78)	(10.84)	(4.52)	(4.72)	(8.75)	(12.69)
Gold	–0.04	–0.36***	0.02			
	(–0.29)	(–5.76)	(0.18)			
Crude oil				0.07	–0.07	–0.06
				(1.24)	(–1.52)	(–1.03)
CDS spread	0.008	0.006	–0.002	0.007	0.008	–0.002
	(1.64)	(1.60)	(–0.67)	(1.35)	(2.08)	(–0.75)
6-mo T-bill rate	0.05	0.05	–0.14	–0.02	0.08	–0.09
	(0.61)	(1.65)	(–2.39)	(–0.18)	(1.75)	(–1.66)
NBUDI	–2.04	–2.04		–1.72	–2.08	
	(–4.20)	(–8.87)		(–3.47)	(–6.68)	
BEI			0.35			0.40
			(5.70)			(4.92)
FRB		0.32			0.24	
		(8.35)			(5.15)	
Fed funds rate	–0.17		0.04	–0.11		0.02
	(–1.66)		(0.67)	(–1.22)		(0.33)
Job postings	0.44	0.31	0.25	0.39	0.38	0.28
	(16.48)	(11.55)	(5.41)	(8.01)	(10.34)	(6.00)
Macro news effect	Yes	Yes	Yes	Yes	Yes	Yes
COVID news effect	Yes	Yes	Yes	Yes	Yes	Yes
Election effect	Yes	Yes	Yes	Yes	Yes	Yes
Observations	118	118	118	118	118	118
Adj *R*-sq	0.9402	0.9666	0.9520	0.9412	0.9608	0.9520

Note(s): *** indicates significance at 1% level; ** indicates significance at 5% level; * indicates significance at 10% level. Variables with moderate-to-severe multicollinearity (VIF>10) are avoided in each model. The coefficient of the fixed effects is not reported. The sample period is the weekly observations from Jan'2020 to Mar'2022. T-statistics values are in parentheses

Source(s): Authors' work

reserve significantly influences the model results here. The relationship is also economically significant. An increase in gold (crude oil) prices by one standard deviation corresponds to an average reduction in sector performance of 1.1% (1.9%) of its sample mean. Like the healthcare sector, the energy sector is also highly sensitive to fluctuations in both commodity prices. The energy sector exhibits such strong sensitivity to both crude oil and gold prices due to its direct revenue dependence on oil markets and its vulnerability to macroeconomic uncertainty signaled by gold price movements. Empirically, a one-standard-deviation increase in crude oil (gold) prices is associated with a 22.0% (5.0%) decline in sector performance relative to its sample mean.

Our results also indicate that the performance of the Industrial sector is negatively associated with gold prices, whereas crude oil prices do not have a statistically significant effect on sectoral returns. This pattern is consistent across the Materials, Real Estate, Financial, and Communication Services sectors, suggesting that increases in gold prices—often indicative of heightened risk aversion or macroeconomic uncertainty—are systematically associated with weaker performance in these economically sensitive sectors. In contrast, the absence of a significant relationship with crude oil prices may reflect sector-specific hedging mechanisms or a muted transmission of oil price shocks during the sample period.

Table 4. Sectoral performance – shifts in returns of the healthcare sector

Variables	(1)	(2)	(3)	(4)	(5)	(6)
Panel IV.A – healthcare sector						
Intercept	108.22	171.76	51.45	145.65	137.73	60.40
	(1.86)	(5.59)	(4.46)	(2.81)	(5.32)	(15.77)
Gold	0.18	–0.19***	0.09			
	(1.45)	(–2.79)	(1.00)			
Crude oil				0.08	–0.07*	–0.03
				(1.59)	(–1.73)	(–0.51)
Panel IV.B – industrial sector						
Intercept	390.57	415.68	52.15	287.50	311.74	42.34
	(7.70)	(15.52)	(5.91)	(6.65)	(12.24)	(12.55)
Gold	–0.21*	–0.44***	–0.07			
	(–1.74)	(–7.23)	(–1.01)			
Crude oil				0.09**	–0.008	–0.05
				(2.01)	(–0.19)	(–1.13)
Panel IV.C – consumer stables sector						
Intercept	116.43	103.24	42.19	221.04	160.56	72.41
	(3.71)	(4.35)	(6.95)	(9.02)	(11.28)	(34.28)
Gold	0.23	0.16	0.30			
	(3.69)	(2.81)	(5.83)			
Crude oil				–0.07	–0.11	–0.09
				(–2.05)	(–3.67)	(–2.51)
Panel IV.D – consumer discretionary sector						
Intercept	442.01	476.96	–6.92	550.36	486.52	41.01
	(4.70)	(8.56)	(–0.43)	(7.44)	(12.65)	(7.09)
Gold	0.33	–0.07	0.49***			
	1.59	(–0.49)	(3.55)			
Crude oil				0.03	–0.15**	–0.20*
				(0.30)	(–2.09)	(–1.88)
Panel IV.E – information technology sector						
Intercept	246.33	297.68	5.98	342.72	285.50	37.49
	(2.68)	(5.68)	(0.35)	(4.41)	(7.33)	(5.75)
Gold	0.28	–0.19	0.33**			
	(1.37)	(–1.56)	(2.37)			
Crude oil				0.009	–0.21***	–0.15
				(0.10)	(–2.95)	(–1.43)
Panel IV.F – materials sector						
Intercept	374.41	367.27	35.89	247.13	310.61	42.07
	(6.44)	(12.78)	(3.50)	(5.74)	(12.12)	(12.40)
Gold	–0.01	–0.25***	0.08			
	(–0.11)	(–3.84)	(0.99)			
Crude oil				0.09	–0.03	–0.09
				(1.52)	(–0.53)	(–1.62)
Panel IV.G – utility sector						
Intercept	47.72	113.48	56.62	143.08	142.30	71.86
	(1.16)	(4.16)	(7.15)	(5.28)	(8.14)	(30.47)
Gold	0.24***	0.05	0.17**			
	(2.68)	(0.76)	(2.57)			
Crude oil				–0.03	–0.10**	–0.10***
				(–0.75)	(–2.58)	(–2.61)

(*continued*)

Table 4. Continued

Variables	(1)	(2)	(3)	(4)	(5)	(6)
Panel IV.H – real estate sector						
Intercept	71.41	193.61	52.99	61.08	111.58	42.80
	(1.14)	(4.56)	(3.74)	(1.06)	(2.85)	(8.08)
Gold	0.03	–0.40***	–0.08			
	(0.23)	(–5.00)	(–0.79)			
Crude oil				0.08	–0.09	–0.03
				(1.42)	(–1.51)	(–0.44)
Panel IV.I – financial sector						
Intercept	419.72	422.58	87.32	113.06	178.33	19.57
	(6.91)	(12.09)	(6.82)	(1.90)	(3.80)	(3.87)
Gold	–0.72***	–0.99***	–0.62***			
	(–4.88)	(–10.92)	(–6.14)			
Crude oil				0.15**	0.03	0.007
				(2.01)	(0.36)	(0.09)
Panel IV.J – energy sector						
Intercept	157.94	23.07	76.09	–155.29	–172.24	23.76
	(1.55)	(0.35)	(4.14)	(–3.05)	(–4.55)	(4.64)
Gold	–0.36	–0.46**	–0.60***			
	(–1.54)	(–2.42)	(–3.70)			
Crude oil				0.57***	–0.50**	0.44
				(8.32)	(–6.71)	(4.86)
Panel IV.K – communication services sector						
Intercept	444.97	569.32	73.66	277.47	369.99	51.61
	(5.06)	(12.99)	(4.57)	(3.79)	(8.04)	(9.26)
Gold	–0.35*	–0.87***	–0.20			
	(–1.85)	(–7.61)	(–1.42)			
Crude oil				0.14*	–0.07	–0.007
				(1.84)	(–0.87)	(–0.08)

Note(s): *** indicates significance at 1% level; ** indicates significance at 5% level; * indicates significance at 10% level. Variables with moderate-to-severe multicollinearity (VIF>10) are avoided in each model. Controls and Fixed Effects are included in each model but not reported. The sample period is the weekly observations from Jan'2020 to Mar'2022. T-statistics values are in parentheses

Source(s): Authors' work

On the other hand, the change in crude oil prices is a significant predictor of the performance of the consumer discretionary sector, while gold prices have no effect. Economically, when crude oil prices increase by one standard deviation, sector performance tends to decline by 3.3% of its sample mean. We find a similar pattern with the Information Technology sector and the Utility sector.

Unlike any other sector, the positive association between gold prices and Consumer Staples likely reflects gold's role as a safe-haven asset during periods of economic uncertainty, which coincides with sustained or increased demand for essential goods. In contrast, rising crude oil prices impose higher production and transportation costs on Consumer Staples firms, thereby exerting downward pressure on their profitability and stock performance during the Covid-19 crisis.

3.4 Robustness check

Addressing endogeneity concerns. The US stock market tumbled rapidly as soon as the news about the COVID-19 virus spread even if the virus outbreak did not hit the United States vehemently in the first three months of 2020. Therefore, there are some endogeneity concerns in our regression.

Addressing simultaneity bias. First, there is a concern for reverse causality that commodity spot prices responded to the movement of the S&P 500 index, but not vice versa. Therefore, we regress commodity prices on the S&P 500 index to determine whether reverse causality is a concern in our regression. In Table 5, we do not find any evidence that fluctuations in gold (crude oil) prices did not affect the movement of the S&P 500 index. Hence, we incorporate time-series lags in our model and find that fluctuations in commodity prices (in models 2 and 5) in one week significantly predict the index movement in the next week during the crisis: A one-standard-deviation decrease in weekly US stock market performance is significantly associated with a subsequent week's increase in gold (crude oil) prices by 2.8% (15%) of their respective sample means.

This finding is consistent with the extant literature findings: spillover effects between commodities and the stock market remain high during the crisis as investors sell shares in the down market and pour investment into the commodity market (Liu *et al.*, 2023; Adams and Gluck, 2015; Ayadi *et al.*, 2021).

Addressing Omitted Variable Bias. Second, there is a concern about omitted variable bias in our regression. Since commodity spot prices depend significantly on global supply and demands, we can conceptualize that geopolitically uncertainty is a significant determinant of commodity prices. We argue that aggregate geopolitical risk exerts a significant influence on commodity prices but has little to no discernible impact on the performance of the US stock market. Unlike commodity prices, US stock market performance is significantly driven by market and economic fundamentals, as evidenced by our baseline results, which are robust to concerns of severe multicollinearity. Our expectation is consistent with the existing literature findings: geopolitical risk negatively impacts trading volume and volatility of both commodity prices and global stock performance (Laubsh *et al.*, 2024; Ding *et al.*, 2021; Liu *et al.*, 2021; Agorki *et al.*, 2022). However, stocks of emerging economies are much more significantly impacted by geopolitical uncertainty than those of developed economies (Zhang *et al.*, 2023). Moreover, geopolitical uncertainty impacts the US stock market primarily when the United States is directly involved in the event (Yilmazkuday, 2024). Otherwise, geopolitical uncertainty influences US stock market performance indirectly through fluctuations in commodity prices. However, it is important to acknowledge that certain US stocks—particularly those with significant multinational exposure—may be more directly affected by such uncertainty. Therefore, our choice of the instrumental variable is at least moderately strong.

Table 5. Test to check for Reverse Causality

Variables	Gold (1)	(2)	(3)	Crude Oil (4)	(5)	(6)
Panel A						
Intercept	362.61	349.77	108.83	259.79	256.52	–20.55
	(10.76)	(14.31)	(16.66)	(3.54)	(3.52)	(–1.70)
S&P 500 index	–0.03	–0.07	0.02	0.25	–0.38	–0.22
	(–0.28)	(–0.98)	(0.18)	(1.27)	(–1.36)	(–1.02)
Panel B						
Intercept	360.75	349.58	101.86	281.38	288.25	–27.40
	(13.84)	(13.40)	(15.59)	(3.91)	(4.14)	(–2.19)
S&P 500 Index	–0.01	–0.46***	0.15	0.18	–0.54*	–0.07
(1-wk lag)	(–0.11)	(–4.26)	(1.38)	(0.83)	(–1.95)	(–0.34)

Note(s): *** indicates significance at 1% level; ** indicates significance at 5% level; * indicates significance at 10% level. Variables with moderate-to-severe multicollinearity (VIF >10) are avoided in each model. Controls and Fixed Effects are included in each model but not reported. The sample period is the weekly observations from Jan'2020 to Mar'2022. T-statistics values are in parentheses
Source(s): Authors' work

To address this omitted variable bias in our single-equation estimation, we follow the Econometrics literature (Angrist and Imbens, 1995; Bollen *et al.*, 2022) to employ a two-stage least squares (2SLS) regression analysis. We use an instrumental variable (Geopolitical risk index, a proxy for geopolitical uncertainty, from the website of Matteo Iacoviello and Caldara and Iacoviello, 2022) for our 2SLS regression analysis. In an untabulated test, the geopolitical risk index does not show significant correlations with other covariates. The robustness of our instrumental variable, the geopolitical risk index, has been confirmed through the literature study and the first stage regression result of 2SLS. The instrument satisfies the relevance condition, with strong correlations to the endogenous explanatory variables (i.e. commodity prices). Since the instrument is not conceptually expected to affect US stock market performance directly—operating instead through the endogenous variables—it satisfies the exogeneity condition, indicating that it has little to no correlation with the structural error term.

In the first stage, we regress commodity prices on the geopolitical risk index and other covariates. In the second stage, we regress the weekly performance of the S&P 500 index on the predicted value of commodity prices from the first regression and other covariates. The following two equations depict the 2SLS estimation procedure:

$$\text{First Stage}: \Delta Gold/Crude\ Oil = \alpha + \gamma_1 * \Delta Geopolitical\ risk\ index + \delta_i \Delta Controls_i + \nu$$

$$\text{Second Stage}: \Delta S\&P\,500\ index = \alpha + \beta_1 \Delta \widehat{Gold/Crude}\ Oil + \delta_i Controls_i + \epsilon$$

The results from the first-stage regression in both panels of Table 6 depict that geopolitical uncertainty is a significant predictor of commodity prices across all models: all else unchanged, a 1% increase in the geopolitical risk index is associated with a 0.05% (0.12%) increase in gold (crude oil) prices in model 2 (model 5). Here, the model numbering is consistent with that in

Table 6. Two-stage least squares regression results with the instrumental variable for geopolitical uncertainty

Panel A: Gold						
	(1)		(2)		(3)	
S&P 500 index	First	Second	First	Second	First	Second
Intercept	353.19	97.32	267.99	283.92	109.83	325.48
	(13.71)	(1.71)	(14.12)	(7.96)	(35.63)	(4.85)
GPR	0.03**		0.05***		0.02**	
	(2.45)		(4.40)		(2.01)	
Predicted_gold		0.69***		–0.36**		–2.51***
		(2.70)		(–2.24)		(–4.09)
Panel B: Crude oil						
	(4)		(5)		(6)	
S&P 500 index	First	Second	First	Second	First	Second
Intercept	319.93	214.0	237.63	243.59	–31.39	31.62
	(6.58)	(5.13)	(5.00)	(9.02)	(–6.96)	(5.89)
GPR	0.12***		0.12***		0.10***	
	(7.14)		(6.00)		(4.36)	
Predict*ed_ crude oil*		0.17*		–0.09		–0.59***
		(1.81)		(–1.41)		(–4.09)

Note(s): *** indicates significance at 1% level; ** indicates significance at 5% level; * indicates significance at 10% level. Variables with moderate-to-severe multicollinearity (VIF >10) are avoided in each model. Controls and Fixed Effects are included in each model, but not reported. T-statistics values are in parentheses. The sample period is the weekly observations from Jan'2020 to Mar'2022
Source(s): Authors' work

Table 3. The results from the second-stage regression indicate that the movement of the S&P 500 index has a statistically significant relationship with the predicted values of gold (crude oil) prices. However, we do not find any clear direction in the relationship for either of the commodity prices. The lack of a clear directional relationship during the COVID-19 crisis likely reflects the combined effects of conflicting economic forces and large-scale policy interventions. While geopolitical uncertainty drove up commodity prices—through supply disruptions in oil and safe-haven demand for gold—stock market responses were mixed due to simultaneous demand collapses and the quantitative easing initiative by the Federal Reserve. These opposing influences might have disrupted the usual links between commodity prices and equity returns, leading to significant but inconsistent effects in direction.

3.5 Additional analysis

Alternative specifications. We consider Gold and Crude Oil proxies for the commodity spot market. To ensure the robustness of our proxies for the commodity spot market, we collected data for alternative commodities such as silver, platinum, and palladium from the London Bullion Market Association (LBMA) for the same period. Then, we regress the movement of the S&P 500 index on each of these alternative commodities for three models. We find the desired result: there is no significant comovement between the index and the alternative commodity spot prices. Therefore, our proxies (Gold and Crude Oil) properly represent the commodity spot market. The results for the alternative specifications can be found in Table 7.

Subsample analysis. Since the S&P 500 index dropped massively from Jan 2020 to Mar 2020 and then started recovering from that point onward, we can reasonably expect the implementation of statewide lockdown initiatives by the US government might have played a big role here. Warned by the increasing number of COVID cases during March 2020, different states started implementing stay-at-home measures. On March 23, 2020, 9 states implemented such orders. The number of states implementing such measures increased to 30 on March 26 and 41 on April 3, 2020 (Jacobsen and Jacobsen, 2020). For simplicity, we assume that the statewide lockdown measures were enforced from the beginning of April 2020. In the first subsample analysis, the treatment period is the pre-lockdown period (i.e. Jan 2020–Mar 2020) and the control period is the post-lockdown period (i.e. the period after Mar 2020). In the second subsample analysis, the treatment period is the post-lockdown period and the control period is the pre-lockdown period. The objective of the subsample analysis is to examine the magnitude of the comovement between the commodity spot prices and the S&P 500 index during the treatment period. The results from the subsample analysis are shown in Table 8.

In Table 8, we find that gold (crude) prices had a significantly stronger effect on the fluctuations of the S&P 500 index during the post-lockdown period (the pre-lockdown period). Here, the model numbering is consistent with that in Table 3. The findings from Panel A depict that a 1% decline in gold prices during the post-lockdown period is associated with a 0.38% greater improvement in the S&P 500 index relative to the pre-lockdown period. On the other hand, the results from Panel B show that a 1% decline in crude oil prices during the pre-lockdown period is associated with a 0.70% greater decline in the S&P 500 index relative to the post-lockdown period.

3.6 Discussion

Our results are consistent with the empirical evidence that dependent variables (i.e. S&P 500 index and Sectoral returns) in some models have a statistically significant relationship with main explanatory variables such as crude oil (e.g. Managi *et al.* (2021) and Kilian and Park (2009)) and gold (e.g. Arfaoui and Rejeb (2017)). Hence, we reject the null hypothesis and conclude that fluctuations in commodity spot prices significantly affected the performance of the US stock market and its constituent sectors during the COVID-19 crisis. The findings from our original regression are robust even after addressing endogeneity concerns such as simultaneity bias and omitted variable bias, alternative specifications, and sub-sample analysis.

Table 7. Alternative specifications: silver, platinum, and palladium as proxies for the commodity spot market

S&P 500 index	Silver			Platinum			Palladium		
Variables	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)	(9)
Intercept	238.57	225.40	32.46	247.73	227.07	28.96	270.68	236.70	50.38
	(4.98)	(7.76)	(2.30)	(5.01)	(8.04)	(1.72)	(5.01)	(8.10)	(4.22)
Silver	0.20	0.08	0.17						
	(1.35)	(0.68)	(1.33)						
Platinum				0.12	0.06	0.21			
				(0.67)	(0.45)	(1.33)			
Palladium							–0.08	–0.05	–0.002
							(–0.55)	(–0.46)	(–0.01)
CDS spread	0.007	0.007	–0.003	0.007	0.007	–0.003	0.008	0.007	–0.002
	(1.47)	(1.81)	(–0.98)	(1.51)	(1.82)	(–1.03)	(1.64)	(1.94)	(–0.73)
6-mo T-bill rate	0.02	0.03	–0.15	0.03	0.04	–0.15	0.05	0.04	–0.13
	(0.28)	(1.02)	(–2.77)	(0.42)	(1.06)	(–2.78)	(0.63)	(1.16)	(–2.33)
NBUDI	–1.92	–1.92		–1.92	–1.92		–1.96	–1.91	
	(–4.23)	(–7.00)		(–4.21)	(–6.95)		(–4.21)	(–7.07)	
BEI			0.35			0.36			0.36
			(5.65)			(5.84)			(5.66)
FRB		0.21			0.21			0.21	
		(5.44)			(5.53)			(5.54)	
Fed funds rate	–0.13		0.05	–0.14		0.05	–0.16		0.04
	(–1.82)		(1.05)	(–1.92)		(1.04)	(–2.03)		(0.67)
Job postings	0.45	0.34	0.26	0.45	0.34	0.27	0.44	0.34	0.25
	(17.09)	(11.36)	(5.53)	(16.09)	(11.22)	(5.58)	(16.31)	(11.07)	(5.36)
Macro news effect	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes
Covid news effect	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes
Election effect	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes
Adj *R*-sq	0.9412	0.9666	0.9520	0.9412	0.9608	0.9520	0.9412	0.9608	0.9520

Note(s): *** indicates significance at 1% level; ** indicates significance at 5% level; * indicates significance at 10% level. Variables with moderate–to–severe multicollinearity (VIF >10) are avoided in each model. The coefficient of the fixed effects is not reported. The sample period is the weekly observations from Jan'2020 to Mar'2022. T-statistics values are in parentheses

Source(s): Authors' work

Table 8. Subsample Analysis: Pre-lockdown vs Post-lockdown

Variables	PRE	POST	PRE	POST	PRE	POST
Panel A: Gold						
Intercept	156.03	163.36	233.91	283.24	53.00	28.35
	(4.94)	(4.05)	(8.99)	(11.26)	(19.60)	(9.59)
Treat	21.86	41.91***	–1.91	45.05***	36.20	28.87***
	(0.42)	(2.71)	(–0.03)	(3.56)	(0.85)	(2.40)
Gold × Treat	–0.49	–0.12	–0.01	–0.39***	–0.60	–0.04
	(–0.51)	(–0.98)	(–0.02)	(–5.79)	(–1.44)	(–0.41)
Controls	Included	Included	Included	Included	Included	Included
Macro news effect	Yes	Yes	Yes	Yes	Yes	Yes
Covid news effect	Yes	Yes	Yes	Yes	Yes	Yes
Election effect	Yes	Yes	Yes	Yes	Yes	Yes
Observations	118	118	118	118	118	118
Adj *R*-sq	0.9665	0.9664	0.9595	0.9670	0.9698	0.9689
Panel B: Crude oil						
Intercept	150.07	125.18	141.01	227.91	54.07	27.03
	(4.74)	(3.39)	(6.33)	(10.38)	(19.52)	(6.14)
Treat	–37.36***	27.23***	–23.77***	2.22	–33.71***	25.45***
	(–5.06)	(5.38)	(–3.43)	(0.33)	(–5.03)	(6.05)
Crude oil × Treat	0.21	0.03	0.55***	–0.15	0.21*	–0.02
	(1.54)	(0.67)	(4.95)	(–4.22)	(1.74)	(–0.44)
Controls	Included	Included	Included	Included	Included	Included
Macro news effect	Yes	Yes	Yes	Yes	Yes	Yes
Covid news effect	Yes	Yes	Yes	Yes	Yes	Yes
Election effect	Yes	Yes	Yes	Yes	Yes	Yes
Observations	118	118	118	118	118	118
Adj *R*-sq	0.9673	0.9662	0.9718	0.9648	0.9704	0.9690

Note(s): *** indicates significance at 1% level; ** indicates significance at 5% level; * indicates significance at 10% level. Variables with moderate-to-severe multicollinearity (VIF >10) are avoided in each model. The coefficient of the fixed effects is not reported. The sample period is the weekly observations from Jan’2020 to Mar’2022. T-statistics values are in parentheses

Source(s): Authors’ work

4. Conclusion

In summary, our findings show that commodity spot prices significantly influence the US stock performance and the performance of all constituent sectors during the COVID-19 crisis. The performance of the Healthcare and Energy sectors is negatively influenced by fluctuations in both gold and crude oil prices. In contrast, only gold prices have a significantly negative effect on the performance of the Industrial, Materials, Real Estate, Financial, and Communication Services sectors. Conversely, only crude oil prices exert a significantly negative influence on the Consumer Discretionary, Information Technology, and Utilities sectors. Uniquely, the Consumer Staples sector is significantly positively influenced by gold prices—a pattern consistent with gold’s role as a safe-haven asset during periods of economic uncertainty, which aligns with sustained or increased demand for essential goods.

Our study is the first to examine the co-movement of commodity spot prices and the US stock market during the COVID-19 crisis. The existing literature finds the connection between derivative products of commodities and stock performance but does not provide any evidence of the co-movement of commodity spot prices and the US stock market. Next, we employ a variety of market and economic factors as controls in our regression analysis to examine the incremental effects of commodity spot prices on the US stock market performance. Finally, we introduce a unique instrumental variable, the geopolitical risk index, that addresses the potential omitted variable bias issues. However, our regression model is not completely free from measurement error since we consider the S&P 500 index a proxy for the US stock market. Our regression model is also susceptible to sample selection bias since we consider our sample period (Jan 2020–Mar 2022) a representative of the actual COVID-19 crisis. Future research may address these issues. Besides, we suggest that future researchers can conduct a comparative analysis in which the comovement of commodity spot prices and the US stock market performance during the COVID-19 crisis would be compared with that during other global health and economic crisis events.

Note

1. The OPEC Reference Basket (ORB), introduced in June 2005, represents a weighted average of spot prices for various crude oils produced by OPEC member countries. We use the ORB from NASDAQ, rather than Brent Crude, to capture a more representative and potentially less biased impact of crude oil prices on the stock market.

References

Adams, Z. and Gluck, T. (2015), "Financialization in commodity markets: a passing trend or the new normal?", *Journal of Banking and Finance*, Vol. 60 No. 11, pp. 93-111, doi: 10.1016/j.jbankfin.2015.07.008.

Agorki, M., Kouretas, G. and Laopodis, N. (2022), "Geopolitical risks, uncertainty, and stock market performance", *Economic and Political Studies*, Vol. 10 No. 3, pp. 253-265, doi: 10.1080/20954816.2022.2095749.

Angrist, J. and Imbens, G. (1995), "Two-stage least squares estimation of average causal effects in models with variable treatment intensity", *Journal of the American Statistical Association*, Vol. 90 No. 430, pp. 431-442, doi: 10.2307/2291054.

Arfaoui, M. and Rejeb, A. (2017), "Oil, gold, US dollar and stock market interdependencies: a global analytical insight", *European Journal of Management and Business Economics*, Vol. 26 No. 3, pp. 278-293, doi: 10.1108/ejmbe-10-2017-016.

Ayadi, A., Gana, M., Goutte, S. and Guesmi, K. (2021), "Equity-commodity contagion during four recent crises: evidence from the USA, Europe and the BRICS", *International Review of Economics and Finance*, Vol. 76 No. 11, pp. 376-423, doi: 10.1016/j.iref.2021.06.013.

Baker, S.R., Bloom, N., Davis, S.J., Kost, K., Sammon, M. and Viratyosin, T. (2020), "The unprecedented stock market reaction to COVID-19", *The Review of Asset Pricing Studies*, Vol. 10 No. 4, pp. 742-758, doi: 10.1093/rapstu/raaa008.

Bianchi, F., Bianchi, G. and Song, D. (2021), "The long-term impact of the COVID-19 unemployment shock on life expectancy and mortality rates (No. w28304)", National Bureau of Economic Research.

Blume, M. and Edelen, R. (2004), "S&P 500 indexers, tracking error, and liquidity", *Journal of Portfolio Management*, Vol. 30 No. 3, pp. 37-46.

Bollen, K., Fisher, Z., Giordano, M., Lilly, A., Luo, L. and Ye, A. (2022), "An introduction to model implied instrumental variables using two stage least squares (MIIV-2SLS) in structural equation models (SEMs)", *Psychological Methods*, Vol. 27 No. 5, pp. 752-772, doi: 10.1037/met0000297.

Boudon, R. (2003), "Beyond rational choice theory", *Annual Review of Sociology*, Vol. 29, pp. 1-21, doi: 10.1146/annurev.soc.29.010202.100213.

Cachanosky, N., Cutsinger, B., Hogan, T., Luther, W. and Salter, A. (2021), "The Federal Reserve's response to the COVID-19 contraction: an initial appraisal", *Southern Economic Journal*, Vol. 87 No. 4, pp. 1152-1174, doi: 10.1002/soej.12498.

Caldara, D. and Iacoviello, M. (2022), "Measuring geopolitical risk", *The American Economic Review*, Vol. 112 No. 4, pp. 1194-1225, doi: 10.17016/ifdp.2018.1222r1.

Callahan, M. (2002), "To hedge or not to hedge... that is the question: empirical evidence from the North American gold mining industry 1996-2000", *Financial Markets, Institutions & Instruments*, Vol. 11 No. 4, pp. 278-288.

Chan, K., Chen, Z., Wen, Y. and Xu, T. (2021), "COVID-19 vaccines and global stock markets", *Finance Research Letters*, Vol. 47 No. 2022, 102774, doi: 10.1016/j.frl.2022.102774.

Chen, N., Roll, R. and Ross, S. (1986), "Economic forces and the stock market", *Journal of Business*, Vol. 59 No. 3, pp. 383-403, doi: 10.1086/296344.

Clancey-Shang, D. (2023), "COVID lockdown, Robinhood traders, and liquidity in stock and option markets", *International Review of Financial Analysis*, Vol. 90 No. 11, 102837, doi: 10.1016/j.irfa.2023.102837.

Cornell, B. (1982), "Money supply announcements, interest rates, and foreign exchange", *Journal of International Money and Finance*, Vol. 1, pp. 201-208, doi: 10.1016/0261-5606(82)90015-8.

Coronado, S., Jiménez-Rodríguez, R. and Rojas, O. (2018), "An empirical analysis of the relationships between crude Oil,Gold and stock markets", *The Energy Journal*, Vol. 39 No. 1, pp. 193-207.

Ding, Q., Huang, J. and Zhang, H. (2021), "The time-varying effects of financial and geopolitical uncertainties on commodity market dynamics: a TVP-SVAR-SV analysis", *Resources Policy*, Vol. 72 No. 8, 102079, doi: 10.1016/j.resourpol.2021.102079.

Erdem, O. (2020), "Freedom and stock market performance during COVID-19 outbreak", *Finance Research Letters*, Vol. 36, 101671, doi: 10.1016/j.frl.2020.101671.

Feldmann, H. (2011), "Stock markets and unemployment in industrial countries", *Applied Economics Letters*, Vol. 18 No. 9, pp. 845-849, doi: 10.1080/13504851.2010.503929.

Hall, R. (2017), "High discounts and high unemployment", *The American Economic Review*, Vol. 107 No. 2, pp. 305-330, doi: 10.1257/aer.20141297.

Jacobsen, G. and Jacobsen, K. (2020), "Statewide COVID-19 stay-at-home orders and population mobility in the United States", *World Medical and Health Policy*, Vol. 12 No. 2, pp. 347-356, doi: 10.1002/wmh3.350.

Jebabli, I., Kouaissah, N. and Arouri, M. (2022), "Volatility spillovers between stock and energy markets during crises: a comparative assessment between the 2008 global financial crisis and the COVID-19 pandemic crisis", *Finance Research Letters*, Vol. 46, 102363, doi: 10.1016/j.frl.2021.102363.

Kang, W., Garcia, F. and Ratti, R. (2024), "Stock market volatility and commodity prices", *Macroeconomic Dynamics*, Vol. 29 No. 2025, e45, doi: 10.1017/s1365100524000324.

Keynes, J. (1937), "Alternative theories of the rate of interest", *The Economic Journal*, Vol. 47 No. 186, pp. 241-252, doi: 10.2307/2225525.

Kilian, L. and Park, C. (2009), "The impact of oil price shocks on the US stock market", *International Economic Review*, Vol. 50 No. 4, pp. 1267-1287, doi: 10.1111/j.1468-2354.2009.00568.x.

Lai, C. and Roy, A. (2005), "The effects of macroeconomic news announcements on mean stock returns", *Proceedings of the Midwest Business Economics Association*, University Of Southern Indiana.

Laubsh, J., Smales, L. and Vo, D. (2024), "The influence of uncertainty on commodity futures returns and trading behaviour", *The Quarterly Review of Economics and Finance*, Vol. 98 No. 12, 101915, doi: 10.1016/j.qref.2024.101915.

Li, J. and Chavas, J. (2023), "A dynamic analysis of the distribution of commodity futures and spot prices", *American Journal of Agricultural Economics*, Vol. 105 No. 1, pp. 122-143, doi: 10.1111/ajae.12309.

Liu, G. and Guo, X. (2022), "Forecasting stock market volatility using commodity spot volatility information", *Resources Policy*, Vol. 75 No. 3, 102481, doi: 10.1016/j.resourpol.2021.102481.

Liu, Y., Han, L. and Xu, Y. (2021), "The impact of geopolitical uncertainty on energy volatility", *International Review of Financial Analysis*, Vol. 75 No. 5, 101743, doi: 10.1016/j.irfa.2021.101743.

Liu, C., Zhang, X. and Zhou, Z. (2023), "Are commodity futures a hedge against inflation? A Markov-switching approach", *International Review of Financial Analysis*, Vol. 83 No. 3.

Malik, F. (2021), “Volatility spillover between exchange rate and stock returns under volatility shifts”, *The Quarterly Review of Economics and Finance*, Vol. 80, pp. 605-613, doi: 10.1016/j.qref.2021.04.011.

Managi, S., Yousfi, M., Zaied, Y., Mabrouk, N. and Lahouel, B. (2021), “Oil price, US stock market, and the US business conditions in the era of COVID-19 pandemic outbreak”, *Economic Analysis and Policy*, Vol. 73 No. 2022, pp. 132-138.

Mazur, M., Dang, M. and Vega, M. (2021), “COVID-19 and the march 2020 stock market crash. Evidence from S&P1500”, *Finance Research Letters*, Vol. 38, 101690, doi: 10.1016/j.frl.2020.101690.

Mensi, W., Shafiullah, M., Vo, X. and Kang, S. (2021), “Volatility spillovers between strategic commodity spot and stock markets and portfolio implications: evidence from developed and emerging economies”, *Resources Policy*, Vol. 71 No. 2021, 102002, doi: 10.1016/j.resourpol.2021.102002.

Mortensen, D. and Pissarides, C. (1994), “Job creation and job destruction in the theory of unemployment”, *The Review of Economic Studies*, Vol. 61 No. 3, pp. 397-415, doi: 10.2307/2297896.

Moschonas, G. (2020), “Paradigm shifts in the light of the past: the 1929 crash, the great recession of 2008 and the COVID-19 crisis”.

Ng, S. (2021), “Modeling macroeconomic variations after COVID-19 (No. w29060)”, National Bureau of Economic Research.

Nguyen, D., Sensoy, A., Sousa, R. and Uddin, G. (2020), “U.S. equity and commodity spot markets: hedging or financialization?”, *Energy Economics*, Vol. 86, 104660, doi: 10.1016/j.eneco.2019.104660.

Pagano, M., Sedunov, J. and Velthuis, R. (2021), “How did retail investors respond to the COVID-19 pandemic? The effect of Robinhood brokerage customers on market quality”, *Finance Research Letters*, Vol. 43 No. 11, 101946, doi: 10.1016/j.frl.2021.101946.

Pindyck, R. (2001), “The dynamics of commodity spot and futures market: a Primer”, *The Energy Journal*, Vol. 22 No. 3, pp. 1-29, doi: 10.5547/issn0195-6574-ej-vol22-no3-1.

Primiceri, G. and Tambalotti, A. (2020), *Macroeconomic Forecasting in the Time of COVID-19. Manuscript*, Northwestern University, Boston, MA, pp. 1-23.

Quan, X. (2022), “The United States stock market trend based on interest rate decisions under COVID-19”, *2022 7th International Conference on Social Sciences and Economic Development (ICSSED 2022)*, pp. 142-146.

Rangel, J. (2011), “Macroeconomic news, announcements, and stock market jump intensity dynamics”, *Journal of Banking and Finance*, Vol. 35 No. 5, pp. 1263-1276, doi: 10.1016/j.jbankfin.2010.10.009.

Rizwan, M., Ahmad, G. and Ashraf, D. (2020), “Systemic risk: the impact of COVID-19”, *Finance Research Letters*, Vol. 34 No. 11, pp. 5266-5308.

Sari, R., Hammoudeh, S. and Soytas, U. (2010), “Dynamics of oil price, precious metal prices, and exchange rate”, *Energy Economics*, Vol. 32 No. 2, pp. 351-362, doi: 10.1016/j.eneco.2009.08.010.

Sigalas, C. (2023), “Impact of COVID-19 lockdowns on retail stock trading patterns”, *Cogent Economics and Finance*, Vol. 11 No. 1, 2188713, doi: 10.1080/23322039.2023.2188713.

Spiegel, M. and Tookes, H. (2021), “Business restrictions and COVID-19 fatalities”, *The Review of Financial Studies*, Vol. 34 No. 11, pp. 5266-5308.

Sujit, K. and Kumar, B. (2011), “Study on the dynamic relationship among gold price, oil price, exchange rate and stock market returns”, *International Journal of Applied Business and Economic Research*, Vol. 9 No. 2, pp. 145-165.

Thompson, C., Kim, R., Aloe, A. and Becker, B. (2017), “Extracting the variance inflation factor and other multicollinearity diagnostics from typical regression results”, *Basic and Applied Social Psychology*, Vol. 39 No. 2, pp. 81-90, doi: 10.1080/01973533.2016.1277529.

Tortorice, D. (2013), “Endogenous separation, wage rigidity and the dynamics of unemployment”, *Journal of Macroeconomics*, Vol. 38, pp. 179-191, doi: 10.1016/j.jmacro.2013.06.002.

Wen, D. and Wang, Y. (2021), "Volatility linkages between stock and commodity markets revisited: Industry perspective and portfolio implications", *Resources Policy*, Vol. 74 No. 2021, 102374, doi: 10.1016/j.resourpol.2021.102374.

White, H. (1980), "A heteroskedasticity-consistent covariance matrix estimator and a direct test for heteroskedasticity", *Econometrica: Journal of the Econometric Society*, Vol. 48 No. 4, pp. 817-838, doi: 10.2307/1912934.

Yilmazkuday, H. (2024), "Geopolitical risk and stock prices", *European Journal of Political Economy*, Vol. 83, 102553, doi: 10.1016/j.ejpoleco.2024.102553.

Zhang, Y., He, J., He, M. and Li, S. (2023), "Geopolitical risk and stock market volatility: a global perspective", *Finance Research Letters*, Vol. 53, 103620, doi: 10.1016/j.frl.2022.103620.

Further reading

Craney, T. and Surles, J. (2007), "Model-dependent variance inflation factor cutoff values", *Quality Engineering*, Vol. 14 No. 3, pp. 391-403, doi: 10.1081/qen-120001878.

Corresponding author
Quazi Nur Alam can be contacted at: quazinuralam@gmail.com