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Testing the Asymmetric Response of China's Stock Returns to Oil Price Dynamics: Does Fear of COVID-19 Matter?

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This study investigates the response of Chinese stock returns to oil prices amidst the COVID-19 pandemic using both linear and nonlinear autoregressive distributed lag (ARDL) models. The results indicate that oil price and the COVID-19 Global Fear Index (*GFI*), respectively, affect stock returns positively and negatively in the short run. While oil price asymmetry matters, Chinese stock returns do not respond to oil price changes and *GFI* in the long run.

I. Introduction

This paper examines how Chinese stock returns, using the Shanghai Composite Stock Price Index, respond to oil price dynamics amidst the COVID-19 pandemic. The main hypothesis is that, given fear of COVID-19, stock market returns in China respond asymmetrically to shocks in the oil price. The theoretical premise or framework that motivates this proposed oil–stock–COVID-19 linkage is the Arbitrage Pricing Theory (APT) proposed by Ross (1976). This theory allows inclusion of indicators of systemic risk, such as the COVID-19 Global Fear Index (*GFI*) and macroeconomic variables like oil price, in predicting expected returns of assets (Haynes, 2020; Iyke & Ho, 2021).

Testing this hypothesis is topical because China is globally recognized as a major oil importer (Hu et al., 2018). Further, as a strong emerging market economy, China's stock market outcomes may be responsive to the dynamics of oil price in the post-COVID-19 era.

There is existing work on the oil–stock nexus (see Basher & Sadorsky, 2006; Fayyad & Daly, 2011; Lin et al., 2014; Narayan & Narayan, 2010; Salisu & Isah, 2017, among others). The COVID-19 pandemic has caused global supply chain disruptions, loss of human resources, and recurring economic and financial shocks (see Salisu & Sikiru, 2020; Zhang et al., 2020, for example), with negative impacts on stock returns in 64 countries (Ashraf, 2020) and for 1,579 firms in China (Alfaro et al., 2020).

The present study employs daily time series of Shanghai Composite stock prices, oil prices, and *GFI* covering the period from February 10, 2020 to January 10, 2021, and finds that, as panic due to the pandemic rises, stock returns are dampened, while changes in the oil price affect stock returns in the short run.[1]

Three research gaps are filled with these findings. First, *GFI* is a new measure of pandemic-caused panic constructed by Salisu & Akanni (2020), and its empirical testing is scarce. Second, previous studies do not explore the predictive importance of the *GFI* index, apart from Salisu, Akanni, et al. (2020), who test the predictive power of this index over commodity price returns. Third, this study uses a country-specific approach instead of a panel approach (see Salisu, Ebuh, et al., 2020), allowing us to explore country-specific effects.

This paper proceeds as follows. The data and methodology are presented in Section II. Section III describes the results obtained and the conclusion drawn. Finally, Section IV details applicable policy prescriptions.

II. Data and Methodology

A. Data

Stock index and oil price data are taken from [www.investing.com]. Two variants of crude oil price (*BRENT* and *WTI*) are used. *GFI* captures the extent of panic (fear) associated with the COVID-19 outbreak. The numbers of global daily infections and deaths are used to construct this index.[2] The choice of sample size is based on data availability, especially *GFI*, at the time of estimation. The data are cleaned to have the same time dimension for all series.

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1 These results were subjected to robustness tests, and the results, especially the CUSUM and CUSUM square plots, are available upon request.

2 The earlier version of the data is contained in Mendeley with a caption "Salisu and Akanni (2020). Global Fear Index Data for the COVID-19 Pandemic [http://dx.doi.org/10.17632/yhs329pd7d.1]" while the updated version can be found in the authors' links in Researchgate.

Table 1: Descriptive Statistics

Statistics	*SSR*	*WTI*	*BRENT*	*GFI*
Mean	0.042	37.859	40.364	56.479
Median	0.048	40.510	42.780	52.420
Maximum	3.278	53.770	59.720	91.190
Minimum	-1.999	-36.980	9.120	9.909
Standard Dev.	0.552	10.588	10.388	12.347
Relative S. Dev	13.143	0.280	0.257	0.219
Skewness	0.458	-2.304	-0.884	1.243
Kurtosis	9.072	13.754	3.369	5.204
Observations	217	217	217	217

This table reported selected descriptive statistics to understand our dataset. The relative standard deviation is obtained as standard deviation divided by the mean of each variable.

B. Model Specifications

Motivated by the APT framework, the stochastic model is, therefore, specified as:

$$SSR_t = a + b_1 OIL_t + b_2 GFI + \epsilon_t \tag{1}$$

where SSR_t is Shanghai Composite stock returns, OIL is crude oil price, and GFI is as already defined.[3] While a denotes the intercept of the model, b_1 and b_2 represent the coefficients of the independent variables. The time dimension of the series is t while ϵ is the error term. Stock returns (SSR) are measured as 100 per cent of differential change (Δ) in the logarithmic values of the Shanghai Composite stock price (SSP). That is:

$$SSR_t = 100(\Delta \log SSP) \tag{2}$$

Having pre-established that the series exhibit different orders of integration (see Table 2), the autoregressive distributed lag (ARDL) framework of Pesaran et al. (2001) is followed for the linear model and is specified as:

$$\begin{aligned} \Delta SSR_t = \ & \alpha + \textstyle\sum_{k=1}^{n} \beta_{t-k} \Delta SSR_{t-k} \\ & + \textstyle\sum_{k=0}^{n} \delta_{t-k} \Delta OIL_{t-k} \\ & + \textstyle\sum_{k=0}^{n} \pi_{t-k} \Delta GFI_{t-k} \\ & + \lambda_1 SSR_{t-k} + \lambda_2 OIL_{t-k} \\ & + \lambda_3 GFI_{t-k} + \varepsilon_t \end{aligned} \tag{3}$$

In Equation (3), k denotes the optimal lag length, while variables with (without) Δ are for the dynamic short-run (long-run) coefficients. In addition to the linear ARDL in Equation (3), it is important to account for nonlinear cointegration (NARDL) of the variables following the Shin et al. (2014) approach by decomposing oil price into positive and negative shocks[4] as shown in Equations (4) and (5).

$$OIL_t^+ = \sum_{j=1}^{t} \Delta OIL_j^+ = \sum_{j=1}^{t} \max(\Delta OIL_j, 0) \tag{4}$$

$$OIL_t^- = \sum_{j=1}^{t} \Delta OIL_j^- = \sum_{j=1}^{t} \min(\Delta OIL_j, 0) \tag{5}$$

By incorporating Equations (4) and (5) into (3), the NARDL model is stated as:

$$\begin{aligned} \Delta SSR_t = \ & \alpha + \textstyle\sum_{k=1}^{n} \beta_{t-k} \Delta SSR_{t-k} \\ & + \textstyle\sum_{k=0}^{n} \pi_{t-k}^+ \Delta OIL_{t-k}^+ \\ & + \textstyle\sum_{k=0}^{n} \pi_{t-k}^- \Delta OIL_{t-k}^- \\ & + \textstyle\sum_{k=0}^{n} \theta \Delta GFI \\ & + \lambda_1 SSR_{t-k} + \lambda_2 OIL_{t-k}^+ \\ & + \lambda_3 OIL_{t-k}^- + \lambda_4 GFI_{t-k} + \varepsilon_t \end{aligned} \tag{6}$$

where OIL^+,and OIL^- are the partial sum decomposed positive and negative changes in oil price, and π^+ and π^- represent their short-run coefficients. It is assumed that the value of the estimate of $\sum \pi_k^+$ differs from the estimate of $\sum \pi_k^-$. Otherwise, there would be no evidence of asymmetries.

III. Result and Discussion

From Table 1, *GFI* exhibits its highest average value (56.5%), followed by *BRENT* at \$40.40 per barrel, *WTI* at \$37.90 per barrel, and stock returns (0.042%). Stock returns record the highest variation. The variables show a mixture of different orders of integration (Table 2, Panel A). With respect to structural break unit root, Table 2 (Panel B) reveals that while *BRENT* is non-stationary at levels with break dates, other variables (*SSR*, *WTI*, and *GFI*) are stationary at levels regardless of breaks.[5]

While *WTI* insignificantly predicts Shanghai stock returns for the study period as shown in the main results of Table 4, *BRENT* does significantly predict it in the nonlinear short-run model. *GFI* significantly reduces Chinese stock returns in the short run. Hence, if the level of panic

3 See Salisu & Akanni (2020) for further description of *GFI*.

4 The Brock–Dechert–Scheinkman (BDS) test for nonlinearity shown in Table 3b provides further justification for the nonlinear model.

5 Narayan and Popp (2010), however, emphasize two breaks. However, only one break date could be identified in each of the two-break models in Table 2 (Panel B).

Table 2: Unit Root Test Results

Panel A: Augmented Dickey Fuller (ADF) and Phillips-Perron (PP) tests

Variables	Augmented Dickey Fuller			Phillips-Perron		
	t-statistic	P-Value	Remark	t-statistic	P-Value	Remark
SSR	-13.719	0.000*	I (1)	-13.696	0.000*	I (1)
BRENT	-13.887	0.000*	I (1)	-13.936	0.000*	I (1)
WTI	-14.948	0.000*	I (1)	-3.780	0.019**	I (0)
GFI	-2.889	0.048**	I (0)	-4.338	0.003*	I (0)

Panel B: Structural break unit root test results

Variables	*SSR*		*BRENT*		*WTI*		*GFI*	
Break types and their T-stat.	IO	AO	I(O)	A(O)	I(O)	A(O)	I(O)	A(O)
	-15.763*	-15.843*	-4.329	-3.872	-7.071*	-7.789*	-4.983**	-5.014**
Break date 1 (TB1)	6th July, 2020	6th July, 2020	5th March, 2020	7th April, 2020	20th April, 2020	26th March, 2020	8th April, 2020	8th April, 2020
Break date 2 (TB2)								
Lag Length (*k*)	0	0	0	9	5	14	0	0

The results are divided into two panels. Panel A has results from the ADF and PP tests, while Panel B has structural break unit root test results. The selected t-statistics were from models with a constant and a time trend are used except for GFI where the ADF test is performed on only a constant. Non-stationary and stationary series are denoted as I(1) and I(0), respectively. The models named IO and AO represent innovational and additive outliers respectively. Finally, *, and ** represent, respectively, statistical significance at the 1% and 5% levels.

(fear) over COVID-19 increases by 1 unit, Shanghai stock return would decline by 0.012% and 0.15% in the ARDL and NARDL short-run models, respectively. Oil price and *GFI* are, however, insignificant in the long run in both models, although a long-run rise in oil prices (*WTI* and *BRENT*) would potentially decrease stock returns linearly and increase stock returns nonlinearly.[6]

In addition, stock returns would be expected to increase in the long run despite increased *GFI*. Thus, *GFI* would matter less for investors in Chinese stocks in the long run, and as time decays, the health system would have increased its capacity to cope with the pandemic (see Alfaro et al., 2020 and Salisu & Vo, 2020 for similar findings). There is a tendency, therefore, for rapid recovery from short-run shocks due to the pandemic (see the error correction terms).

Further, asymmetry matters in the oil–stock returns link post-COVID-19 in China (see the Wald test for asymmetry). The overall implication is that the response of China's stock market returns to oil price shocks amidst COVID-19 is a short-run phenomenon.

IV. Conclusion and Policy Prescriptions

This paper investigates how China's stock returns have responded to oil price dynamics post–COVID-19. In the short run, changes in oil price (*BRENT*) predict stock returns positively, while *GFI* decreases stock returns. While oil price asymmetry matters, Chinese stock returns do not respond to changes in the oil price and *GFI* in the long run. Hence, the oil–stock–GFI linkage in China is a short-run phenomenon. Among possible policy alternatives, a comprehensive health policy that would aid speedy recovery from the shocks of the pandemic is necessary to strengthen high stock returns in China. Other researchers could focus on the oil–stock–COVID-19 linkage with structural breaks.

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6 Note that long-run results from dynamic models (including ARDL and VAR) are interpreted in reverse form of the accompanying statistical signs of the estimated coefficients.

Table 3: The Bound test and nonlinearity test results

Panel A: Bounds test for cointegration					
Linear ARDL (Symmetric) Model for *WTI* Null: No long run relationship			Linear ARDL (Symmetric) Model for *BRENT*		
Test Statistic	Value	*k*	Test Statistic	Value	*k*
F-statistic	65.65	2	*F*-statistic	71.40	2
Pesaran et al. (2001) Critical value bounds			Pesaran et al. (2001) Critical value bounds		
Significance	I(0)	I(1)	Significance	I(0)	I(1)
1%	6.34	7.52	1%	6.34	7.52
5%	4.87	5.85	5%	4.87	5.85
10%	4.19	5.06	10%	4.19	5.06
Narayan (2004) Critical value bounds			Narayan (2004) Critical value bounds		
Significance	I(0)	I(1)	Significance	I(0)	I(1)
1%	3.42	7.84	1%	3.42	7.84
5%	2.23	5.43	5%	2.23	5.43
10%	1.74	4.46	10%	1.74	4.46
Nonlinear ARDL (Asymmetric) Model for *WTI* Null: No long run relationship			Nonlinear ARDL (Asymmetric) Model for *BRENT*		
Test Statistic	Value	K	Test Statistic	Value	K
F-statistic	51.24	3	F-statistic	54.75	3
Pesaran et al. (2001) Critical value bounds			Pesaran et al. (2001) Critical value bounds		
Significance	I(0)	I(1)	Significance	I(0)	I(1)
1%	5.17	6.36	1%	5.17	6.36
5%	4.01	5.07	5%	4.01	5.07
10%	3.47	4.45	10%	3.47	4.45
Narayan (2004) Critical value bounds			Narayan (2004) Critical value bounds		
Significance	I(0)	I(1)	Significance	I(0)	I(1)
1%	3.30	7.01	1%	3.30	7.01
5%	2.20	4.96	5%	2.20	4.96
10%	1.75	4.14	10%	1.75	4.14

Panel B: The BDS test results for nonlinearity				
Variables	*SSR*	*BRENT*	*WTI*	*GFI*
Dimension	BDS Statistic	BDS Statistic	BDS Statistic	BDS Statistic
2	0.008 (0.175)	0.188 (0.000)*	-4.23E-05 (0.9446)	0.168 (0.000)*
3	0.022 (0.019)**	0.319 (0.000)*	-0.0001 (0.9250)	0.285 (0.000)*
4	0.029 (0.010)*	0.408 (0.000)*	-0.0003 (0.9096)	0.361 (0.000)*
5	0.032 (0.006)**	0.467 (0.000)*	-0.0004 (0.8962)	0.410 (0.000)*
6	0.033 (0.004)*	0.506 (0.000)*	-0.0006 (0.8841)	0.439 (0.000)*

This table has two sets of results. Panel A has the results from the bounds test for cointegration, while Panel B has results on the BDS nonlinearity test. The unrestricted intercept and trend critical values of the bounds test are obtained from Pesaran et al. (2001) and Narayan (2004) based on the numbers of the regressors (k). Finally, * and ** denote statistical significance at the 1% and 5% levels, respectively, and the p-values of the BDS statistics are in the parentheses.

Table 4: The main regression results

Variable	Linear or Symmetric (ARDL) Model		Nonlinear or Asymmetric (NARDL) Model	
	WTI	*BRENT*	*WTI*	*BRENT*
Short run Coefficients				
Δ(*WTI*)	0.003 (0.485)			
Δ(*WTI*(+)			0.001 (0.696)	
Δ(*WTI*(-)			-0.001 (0.691)	
Δ(*BRENT*)		0.084 (0.000)*		
Δ(*BRENT*(+)				0.107 (0.000)*
Δ(*BRENT*(-)				0.110 (0.000)*
Δ(*GFI*)	-0.016 (0.009)**	-0.014(0.016)**	-0.015 (0.012)**	-0.014 (0.016)**
ECT(-1)	-0.954 (0.000)*	-0.960 (0.000)*	-0.979 (0.000)*	-0.969 (0.000)*
Wald test for Asymmetry			1.178 (0.310)	9.717 (0.000)*
Long run Coefficients				
C	0.069 (0.804)	-0.032 (0.912)	0.111 (0.745)	-0.075 (0.7903)
WTI	0.003 (0.484)			
WTI(+)			0.005 (0.185)	
WTI(-)			-0.002 (0.690)	
BRENT		0.003 (0.459)		
BRENT(+)				0.001 (0.739)
BRENT(-)				0.005 (0.265)
GFI	-0.002 (0.499)	-0.001 (0.818)	-0.003 (0.412)	0.000 (0.984)
Wald test for Asymmetry			0.088 (0.767)	8.940 (0.000)*
Diagnostic statistics				
Breusch-Godfrey LM test	0.535 (0.587)	0.472 (0.625)	0.118 (0.889)	0.731 (0.483)
Breusch-Pagan Godfrey	0.457 (0.767)	0.219 (0.954)	0.578 (0.748)	0.551 (0.795)
Ramsey Reset Test	4.131 (0.043)**	3.069 (0.081)***	4.698 (0.031)**	0. 443 (0.507)

This table reports the main regression results. Panel A has short-run coefficients, Panel B has long-run coefficients, and Panel C contains diagnostic test results. Finally, *, **, and *** denote statistical significance at the 1%, 5%, and 10% levels, respectively, with probability values of the coefficients shown in the parentheses.

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