Time-Varying Return Predictability and Adaptive Behavior in The U.S. Commodity Markets During COVID-19

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ABSTRACT

The study investigates the time-varying efficiency of the four most commonly traded international commodities from the U.S. Chicago Board of Options Exchange (CBOE) over a more extended period as well as during COVID-19. The study also explores how adaptive behavior of returns induces profitable opportunities in the commodity markets. Daily returns of commodity indices (gold, silver, oil, metal) are divided into subsamples of six years, to apply a battery of linear/nonlinear tests. The study uncovers the linear and nonlinear serial dependence in returns from commodities and finds evidence of time-varying volatility, thus consistent with the Adaptive Market Hypothesis over the full sample period. Moreover, returns from all the commodities are highly volatile and predictable during COVID-19.

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INTRODUCTION

Investors select investments based on their risk-return objectives. Risk-return optimization is key to investment and portfolio performance. Among the vast investment avenues available, commodities are a distinct asset class that enriches portfolio selection and management. Different aspects of commodities have received sufficient attention from researchers (see Urquhart, 2017; Shahid et al., 2020). One of the intriguing concerns has been commodity market efficiency, which deals with the predictability of commodity market prices in financial markets. After decades of research, market efficiency remains an important topic. The market is only considered efficient once the security prices exhibit their historical trading information while investors remain unable to earn abnormal profits, asset prices follow the martingale process (Fama, 1970). Market efficiency and anomalies have been widely studied with results generally favoring the Efficient Market Hypothesis (EMH). Contrarily, several statisticians and financial economists now acknowledge that returns from securities depict seasonal effects, and as a consequence, partial predictability is plausible (Kim et al., 2011; Smith, 2012; Lim et al., 2013; Hiremath and Kumari, 2014; Urquhart et al., 2013; Urquhart, 2017; Shahid et al., 2019b). Though numerous studies report that security prices follow a random-walk progression, there have been alternative views on whether financial markets are efficient or inefficient. Instead of testing absolute EMH, Campbell et al. (1997) stress that the concept of relevant efficiency could be more valuable. Through this, we could measure the levels of efficiency instead of identifying the perfect efficiency.

The literature on commodities uses a variety of econometric models and the focus of interest is to detect predictability through EMH (Urquhart et al., 2013; Urquhart, 2017).The hypothesis (AMH) proposed by Lo (2004) has largely been ignored in the commodities literature (Shahid et al., 2020). AMH is an enhanced form of EMH to investigate the varying levels of predictability in returns. AMH is based on well-known principles of evolution, adaptation, competition, and natural selection and is an alternative to EMH. AMH signifies that i) markets pass through cycles of good and bad performances thus, switching between inefficiency and efficiency, ii) risk-reward relationship and investors' preferences change over time as forced by natural selection, and iii) financial technological advancement, survival of fittest and market evolution are the main pillars in forecasting (Lo, 2012). Therefore, predictability of returns exhibits cyclic patterns due to information technology, macroeconomic institutions, and market regulations and policies thus indicating the presence of AMH. Similarly, Kim et al. (2011) report that markets fluctuate, and their efficiency is based on certain conditions. AMH exhibits forecasting patterns that exist in the market and arise from time to time. Hence, this study examines the predictability (efficiency) of commodities using AMH.

Apart from their returns, commodities have also been studied for their potential for hedging and diversification. The missing piece has been the testing of AMH for commodities (see for example Ramirez et al., 2014; Ramirez et al, 2015). Though some research has been done to test the AMH (see for example Asian markets studied by (Lim et al., 2008; Neely et al., 2009), US markets studies by (Ito and Sugiyama, 2009; Kim et al., 2011; Alvarez-Ramirez et al., 2012,) Japan by (Noda, 2012); US foreign exchange market by Charles et al. (2012); some major indices have done by (Urquhart and Hudson, 2013).

The focus of this study is to examine AMH in the commodities market by exploring both linear and non-linear serial dependencies in the four most traded commodities (silver, oil, aluminium, and gold) at the Chicago Board of Options Exchange (CBOE). The closing price of these commodities has been selected and data ranges from (Silver 1977-2018; Oil 1989-2018; aluminium 1977-2018; and gold 1983-2018). Data has been sourced from DataStream (Thomson Reuters Professional). The selected period is suitable for a wide-range inquiry as the era of high-low volatilities like Asian Financial-Crisis, Dotcom-Crisis, Global Financial-Crisis and European Sovereign Debt-Crisis periods have been captured in this period. Moreover, to validate the assumption of AMH, we also select the COVID-19 period.

Autoregressive (AR) models, Autoregressive moving averages (ARIMA), Moving-Averages models, and dynamic and transfer function models have been used to investigate the prices of commodities. On the other hand, contemporary studies of (Adrangi and Chatrath, 2003; Benavides, 2004; Tansuchat et al., 2009) use GARCH-model while in some studies BDS (Brock, Dechert and Scheinkman statistic) test, neural-networks test, Lyapunov-exponents test, and correlation exponent are used to explore the chaotic behavior of commodity series (see studies of Blank, 1991; Yang and Brosen, 1993; Ahti, 2009; Tejeda and Goodwin,

2009). However, we test for both linearity and non-linearity in full as well as sub-samples to integrate the idea of AMH.

This paper enhances the existing body of knowledge on AMH and commodities as i) it investigates the returns from most popular and commonly traded commodities on CBOE, ii) it examine the returns from time-varying perspectives using AMH, iii) it examines the linear and non-linear predictability for commodities over a longer period, iv) it uncovers the profitable opportunities through adaptive behavior of returns and v) it explores the predictability of returns during COVID-19 period. Though Shahid et al. (2020) investigate the linear and nonlinear predictability of the commodities, their study is limited to crises periods only, while a longer period and sub-samples analysis may provide better results.

We find that the predictability of returns from commodities possesses linear and nonlinear dependence and it arises and disappears over time. Similarly, AMH exhibits a more accurate explanation of the behavior of commodities return than EMH. The structure of the research is as follows: section 2 presents the relevant literature; Section 3 discusses the data and methodology followed by the discussion of results in section 4. Lastly, section 5 summarizes the findings and concludes the paper.

LITERATURE REVIEW

Commodities have been studied often for their hedging and diversification benefits through the time-varying correlation property. The correlation is induced by the composite interactive impact associated with the supply-demand shocks. Due to the desired characteristic, commodities are considered as the supply of wealth during the eras of financial crises, a period where the value of many other assets plunges. These commodities may act as assets having characters to diversify the portfolio during the huge economic and political laps and stock market crashes.

The recent trends in both the financial and commodity markets and financialization of the commodities provide the opportunity to hedge, diversify and manage the risk of individual and portfolio investments (Tang and Xiong, 2012; Silvennoinen and Thorp, 2013). For example, gold possesses unique qualities and it qualifies well for the medium of exchange, a unit of value, and a store of wealth criteria (Solt and Swanson, 1981). Besides, silver has likewise been utilized as an important commodity in the industry as well as a financial instrument for portfolio investments. A multipurpose metal, Silver has gained a significant position in the current age of technological innovations as it is a central component of electronics, solar energy and medical equipment, and batteries. Silver is continuing to play an important role as its trading is expanding and its markets are widening globally. Another metal, platinum which is a rarely found metal, by 2006, its production has peaked to about 514 tons per annum. Due to its standardized form and purity, it is also internationally accepted as a medium of exchange like gold and silver. Platinum also harnesses the special physical features of metal for industrial manufacturing usage, especially in the area of automotive and jewelry. Platinum contributes to approximately 20 percent of consumer goods which further adds to their importance. Likewise, metals, oil also plays a significant role in the world economy, and its often modeled with other assets (Vivian and Wohar, 2012). The fluctuations in oil prices influence the prices of other commodities as well as stock and bonds. According to (Urquhart, 2017), despite commodities comprising of exclusive properties, their price stability is extremely reliant on prevailing political and economic conditions. A plethora of extensive empirical literature depicts that the risks can be hedged in the stock market by holding commodities. The correlation of commodities with stocks, enables the managers to stabilize the portfolio volatility and avert risk by readjusting their stock positions.

Ciner et al. (2013) identify the inadequacies in early studies as commodities have often been ignored and the focus has been on currencies, bonds, and equities. For instance, a commodity such as gold is considered to be a safe commodity for eras of financial crises and inflation-related issues. Globally, gold has been used more as a conventional investment tool for keeping as a safeguard from financial calamities (Baur and McDermott, 2010; Daskalaki and Skiadopoulos, 2011). The decision to invest in commodities should be prioritized, after vigorous analysis, to make sure that financial risks are mitigated properly (Eswara, 2015). Typical to prior discussion, Ciner et al. (2013) examine the hedging role of dollars (USD), stocks, bonds, oil, and gold as safe-haven in markets in the UK and USA. They study the dataset the period from January 1990 to

June 2010 daily. The study alluded that gold is considered to be the hedger as well as a haven under study. Further, the role of four well-known commodities gold, platinum, silver, palladium is examined by (Lucey and Li (2015). They find that when gold's status of safe heaven is doubtful, other commodities take up a similar role for financial safeguard purposes within the USA. While referring to the seasonal effect by taking the monthly average returns of gold from 1980 -2010, Baur (2013) observes that during autumn time customers demand gold upsurges, especially during the wedding season. Arouri et al. (2013) further explain that while in the long and short-run historical information is futile to make any prediction so, investors should use the past information by designing appropriate investment strategies to forecast and also taking into account the seasonal and other geopolitical effects as well. Pierdzioch et al. (2014) examine the short-term monthly excess returns from commodities. Their findings project that holding commodities for the long-term generates superior profits and investment performance through buy and hold strategy in comparison to committing to short-term transactions. They further conclude that the market for commodities is capable depending on the study variables, while the real-time predicting tactic can only guide simple trading rules that generate inferior investment performance.

Batten et al. (2008) examine the palladium, gold, platinum, and silver using the data comprising the five minute-frequency (Intraday). By examining the stylized facts, correlation, and interaction between returns and their volatility, they find a substantial increase in the trading of each commodity over time. Moreover, they observe price efficiency, increased liquidity, and narrowed trends in bid/ask spread. Charles et al. (2012) explore that political and economic circumstances are directly related to silver and gold. They use automatic-portmanteau and VR tests to inspect the time-varying abilities of commodities return. They find that possibility for a prediction about commodities' return fluctuate over time as the predictability of gold and silver returns have diminished, thus supporting the weak form of EMH. Using the daily spot prices over the period 1968-2014 from 28 emerging and developed commodities markets, Ntim et al. (2015) investigate the Random Walk Hypothesis (RWH) and Martingale Sequence Difference (MDS) hypothesis through VR test. They find that all the few markets support weak for both the hypotheses, while some markets are efficient with MDS but not with RWH. Moreover, some of the sample countries' markets are not efficient at all. The rejection of market efficiency is more in emerging markets as compared to developed markets. Using Markov-Switching CAPM and traditional (CAPM) in markets of UK and US, He et al. (2018) investigate whether gold acts as a safe haven during the era of an extreme market crash and observe that gold is not evidenced as a portfolio diversifier in US and UK. Intraday technical trading rules and their predictive power are examined by Batten et al. (2018) in commodities. They find silver returns are significantly predictable through the trading rules but returns from gold are not predictable. He et al. (2019) compared the risk premium of Chinese commodity markets and compare them with the commodity markets of the USA. They find that Chinese commodity markets are better explained by three important investment factors like market, carry, and momentum in the series of returns over time. They further find that the premium on returns from commodities is weaker in China as compared to US commodities markets. Moreover, they find a time-varying serial correlation in cross-sectional and time-series returns in commodity markets of China and the US. Shahid et al. (2019b) using linear econometric models examine the link between AMH and linear dependencies of metal, gold, and silver. Runs test, Variance ratio, and autocorrelation test reveal that AMH allows the predictability of commodity markets of the US to vary over time. They report that investors can use this time-varying information to model their portfolios while hedging commodities against other assets. With the application of linear and nonlinear models, Shahid et al. (2020) assess whether AMH holds during crisis periods. They utilize a period spanning major crises includes; European Sovereign Debt-Crisis periods, Global Financial-Crisis, Asian Financial-Crisis, and Dotcom-Crisis. They report that AMH is the best explanation of the predictability of returns from commodities during crisis periods.

COVID-19 and Returns from Financial Markets

None of the infectious diseases causes a huge jumping swing in returns from financial markets as COVID-19 has initiated in the return series. Baker et al. (2020) report that financial markets of the US and other countries are evident of mild effects of pandemics, while COVID-19 brings a fall in returns and upward trends in the volatility. Due to COVID-19, social distancing policy, containment mandates,

and travel restrictions are imposed subjective to healthcare rationale. These commands bring huge damages to the global economy. The recent volatility levels of financial markets mirror the future expected damages as studies (Al-Awadhi et al., 2020; Ashraf, 2020; Liu et al., 2020; Onali, 2020) also reflect the same evidence. There observed a double-figure decline in major stock markets and a 30% decline posted by S&P 500 in just 16 trading days. COVID-19 puts doubt on the validity of EMH while having some implications for AMH as AMH states that certain conditions/crises dictate the movements in prices of financial assets. Similarly, COVID-19 encompasses a few episodes of varying returns from financial markets (Wagner, 2020).

The epidemic (Li et al., 2020) and pandemic (Ashraf, 2020) phases of COVID-19 initiate a swing in economic activities as the lives of billions of people are affected by the disease spread around the globe (Dunford et al., 2020). Many studies find the volatility of financial markets; Gates (2020) finds severe outbreaks of COVID-19 have badly affected the financial markets of countries like China, Iran, Italy, France, Spain, the UK, and the USA. Similar results are found by Al-Awadhi et al. (2020) in China, Liu et al. (2020) in the UK, Italy, Germany, USA, Singapore, Korea, and Japan, Onali (2020) in Dow Jones and S&P 500, Papadamou (2020) in Asian markets, Ali et al. (2020) in bitcoin, bond and commodity indices, Gunay (2021) in currency markets. Motivated from the mentioned studies the current study is aimed to explore the volatility of globally popular commodities like Gold, Metal, oil, and silver. Moreover, all the studied commodities show evidence of high volatility during the COVID-19 period (see Figure 4)

DATA AND METHODOLOGY

The daily returns data for the commodities have been selected for the oil index from January 1[st,] 1989 to December 31[st,] 2018, for the gold index from January 1[st,] 1983 to December 31[st,] 2018, for silver and metal indices from January 1[st,] 1977 to December 31[st,] 2018. The selection of start date is based on the availability of data. We employ the empirical linear and nonlinear tests on the data of selected commodities for this study over the mentioned periods. Based on the literature (see for example Urquhart and Hudson, 2013; Ghazani and Araghi, 2014; Ramirez et al., 2015; Shahid and Sattar, 2017) we divide the data set into sub-samples to integrate the idea of AMH. The 6 yearly sub-samples offer adequate observations to provide reliable results to explore the linear and nonlinear time-variant nature of returns from commodities

The returns from each series are computed by:

$$r_t = [ln(P_t) - ln(P_{t-1})] \times 100 \tag{1}$$

where at time t, the natural logarithm for the index is represented by $ln(P_t)$, on the other hand at time $t-1$, the natural logarithm is denoted by $ln(P_{t-1})$. The descriptive results are portrayed in Table-1 for log returns from commodities. The table shows results for full as well as sub-samples. The full sample for each commodity depicts a greater magnitude of extreme positive returns as compared to negative returns. Returns are evidence of leptokurtic series as excess kurtosis is exhibited by full and sub-samples. The returns from each series are found to be non-normal as the test statistic of the Jarque-Bera test is statistically significant at 1%. On the other hand, except for oil, all other commodities produce positive mean returns during COVID-19 and all the series are evident pf non-normality. Based on the study of (Urquhart and Hudson 2013; Shahid et al., 2019a), we employ a battery of tests comprising linear and nonlinear tests to identify the swing (episodes) in the behavior of commodity returns.

Linear tests

Autocorrelation

From linear tests, the most reliable and appropriate tool is the autocorrelation test to examine the independence of a series of returns (random variable). Usually, autocorrelation arises when different

disturbances have non-zero correlations and covariances i.e. for all $\neq j$, $Cov\left(\varepsilon_i, \varepsilon_j\right) = \sigma_{ij}$, where ε_t is the disturbance value in i^{it} observation:

$$\rho_k = \frac{\gamma_k}{\gamma_o} \tag{2}$$

The positive-autocorrelation is inferred by $\rho > 0$, negative-autocorrelation is represented by $\rho < 0$, while no correlation is inferred by $\rho = 0$ which indicates a random walk process and implies the null hypothesis of this test.

Runs test

Contrary to the autocorrelation test, the Runs test does not demand that a series should be normally distributed (Poshakwale, 1996). According to Siegel (1956), a run is a group of sequences or variables of similar value. The expected number of Runs can be computed as:

$$E\left(\mu\right) = \frac{2PN(P + N)}{(P + N)} + 1 \tag{3}$$

where P is symbolized to present the positive number of runs and a negative number of runs are represented by N. The variance of runs is computed by:

$$\sigma^2 = \frac{2PN(2PN - P - N)}{(P + N)^2 \, (P + N - 1)} \tag{4}$$

The independence of a series of returns is the null hypothesis of this test. Once the z-value is greater than the critical values the null hypothesis is rejected.

Variance-Ratio Test

Lo and MacKinlay (1988) present the Variance Ratio (VR) test to gauge the predictability of asset prices to measure the variance of increments (RWI hypothesis) of a random walk (Hoque et al., 2007). The basic underlying assumption of this test is the variance of k periods return is equivalent to the k times variance of a period in a random walk progression showing the variance of returns from 10 days period is equivalent to 10 times-variance of its one-day return. Also, r_t is the VR test having k holding period can be calculated by using the formula:

$$VR(k) = \frac{\sigma_k^2}{k\sigma^2} \tag{5}$$

The r_t infers the asset's returns relevant to t period, signifying $t = 1,2,3....T$. while for k period the variance is $\sigma_k^2 = r_t + r_{t-1} + \cdots + r_{t-k+1}$ is represented by:

$$VR(k) = 1 + 2 \sum_{j=1}^{k-1} (1 - \frac{j}{k})\rho(j) \tag{6}$$

where $\rho(j)$ signifies the r_t autocorrelation for j order and $1 + t$ is the variance ratio with increasing and decreasing weights of returns from assets. As $\rho(j) = 0$ showing zero correlation in series of returns hence, "the null hypothesis of variance ratio test is that: VR equals to 1 for all $k's$". Under the assumption of homoscedasticity, the null hypothesis $V(k) = 1$, if x_t is $i.i.d.$ The test statistic $M_1(k)$ is given by:

$$M_1(k) = \frac{VR(x; k) - 1}{\Phi(k)^{\frac{1}{2}}} \tag{7}$$

The test statistic follows the standards asymptotically normal distribution, the asymptotic variance $\Phi(k)$ can be given by:

$$\Phi(k) = \frac{2(2k-1)(k-1)}{3k} \tag{8}$$

As the returns exhibit conditional heteroskedasticity, Lo and MacKinlay (1988) accommodate this by proposing the robust heteroscedasticity test statistic $M_2(k)$:

$$M_2(k) = \frac{VR(x;k) - 1}{\Phi^*(k)^{1/2}} \tag{9}$$

Under the null hypothesis $V(k) = 1$, the test statistic asymptotically follows the standards of the normal distribution, where:

$$\Phi^*(k) = \sum_{j=1}^{k-1} \left[\frac{2(k-j)}{k} \right]^2 \delta(j) \tag{10}$$

$$\delta(j) = \frac{\left\{ \sum_{t=j+1}^{T} (x_t - \hat{\mu})^2 (x_{t-j} - \hat{\mu})^2 \right\}}{\left\{ \left[\sum_{t=1}^{T} (x_t - \hat{\mu})^2 \right]^2 \right\}} \tag{11}$$

The M2(k) test can be applied to a series of stock returns and for standard normal distribution. We present results for 2, 4, 8, and 16 k holding periods.

Nonlinear tests

Earlier debate sheds light on detecting linear dependency in return series from commodities through conventional linear tests. Amini et al. (2010) report that in the absence of linear dependencies the returns series still may have some nonlinear serial dependencies that gained attention in the literature (Urquhart and Hudson, 2013; Ghazani and Araghi, 2014; Shahid et al., 2020). Inherent nonlinearity is the basic characteristic of time series, so the following non-linear methods are more consistent to test the efficiency of the commodity markets through determining the levels of dependencies in the series compared to traditional linear methods (Alharbi, 2009).

<u>**McLeod Li Test**</u>

McLeod and Li (1983) propose a portmanteau test to detect nonlinear serial dependencies (ARCH effects) in series. The following test-statistic compute whether the "squared autocorrelation function of the series of returns is non-zero":

$$Q(m) = \frac{n(n+2)}{n-k} \sum_{k=1}^{m} r_a^2(k) \tag{12}$$

$$r_a^2(k) = \frac{\sum_{t=k+1}^{n} e_t^2 e_{t-k}^2}{\sum_{t=1}^{n} e_t^2} \quad k = 0,1,\dots,n-1 \tag{13}$$

where squared residuals of autocorrelation are represented by r_a, while e_t^2 is attained by employing a suitable econometric model in the return sequence. If the independent and identical distribution is exhibited by the series of returns i.e., e_t, then "asymptotic distribution" of $Q(m)$ is m degree of freedom X^2. The null of this test implies that the equity returns are independent.

<u>**Engle LM test**</u>

To detect ARCH disturbances, Engle (1982) proposes a Lagrange Multiplier test. For heteroskedasticity, he tests the residuals of $AR(p)$ models. The test-statistic of Engle LM Engle (1982) is based on R^2 and calculated from "auxiliary regression" which is as follow:

$$\hat{e}_t^2 = \alpha_0 + \sum_{i=1}^{p} \alpha_i \, \hat{e}_{t-i}^2 + v_t \tag{14}$$

where e represents the residual from the $AR(p)$, pre-whitening model. The traditional $F-statistic$ test is used for regression on the squared residuals as:

$$F\ statistic = \frac{RRSS - URSS}{URSS} \times \frac{T-K}{m} \tag{15}$$

where, from restricted regression, $RRSS$ is the residual sum of the square. While from unrestricted regression $URSS$ is the residual sum of squares and m denotes the number of restrictions. T represent the number of observations while in the unrestricted regression K represent the number of regressors. Under the linear generating mechanism, the null hypothesis for e_t, NR_2 for the regression is asymptotically $X^2(P)$ distributed.

Tsay test

To detect quadratic-serial dependencies in the data, Tsay (1986) offers a Tsay test. "Let $K = k(k-1)/2$ is a column vector that comprises all the potential cross products of the form $r_{t-1} r_{t-j}$ where $\varepsilon[i, k]$". So that:

$$v_{t,1} = r_{t-1}^2; \ v_{t,2} = r_{t-1} r_{t-2}; \ v_{t,3} = r_{t-1} r_{t-3}; \ v_{t,k+1} = r_{t-2} r_{t-3}; \ v_{t,k+2} = r_{t-2} r_{t-4} \dots \dots \dots v_{t,k} = r_{t-k}^2 \tag{16}$$

where $\hat{v}_{t,i}$ is the projected value of $v_{t,i}$ in the subspace orthogonal to $r_{t-1}, \dots, r_{t-k}$, representing residuals of regression from $v_{t,i}$ on $r_{t-1}, \dots, r_{t-k}$.

While $\gamma_1, \dots, \gamma_k$ are computed through the following parameters of regression:

$$r_{t-1} = \gamma_0 + \sum_{i=1}^{k} \gamma_i \, \hat{v}_{t,i} + \varepsilon_t \tag{17}$$

To testify that $\gamma_1, \dots, \gamma_k$ are all zero, this test uses traditional $F-statistic$.

BDS Test

Brock et al. (1996) propose a portmanteau test: BDS to spot time-varying dependencies in return for the series. BDS test is named after the following authors: Willium A. Brock, W. Davis Dechert and J. A. Scheinkman. This test uses the correlational dimensions of (Grassberger and Proceaccia, 1983) on a series with observation $\{x_1 \dots x_n\}$ and history of m such as $x_{mt} = (x_t, x_{t-1}, \dots \dots \dots x_{t-m+1})$, while for ε distance and "embedding dimension (*m)*" the correlation integral $\{C_m(n, \varepsilon)\}$ can be computed as:

$$C_m(n, \varepsilon) = \frac{2}{(n-m)(n-m+1)} \sum_{S=1}^{n-m} \sum_{t=S+1}^{n-m+1} I_m(x_S, x_t, \varepsilon) \tag{18}$$

Table 1 Offers statistical descriptions for commodities

Sample-period	Mean	Maximum	Minimum	S.D	Skewness	Kurtosis	Jarque-Bera	Sum	N
				Panel A: Gold					
COVID-19	**0.090**	**5.60**	**-5.06**	**1.31**	**-0.22*****	**7.00*****	**183.38*****	**25.46**	**272**
Full-Sample	0.014	8.82	-9.81	1	-0.268***	9.708***	20870.7***	114.57	9388
1983-1988	-0.02	7.79	-5.76	1.48	0.1580**	5.939***	570.005***	-38.75	1565
1989-1994	-0.01	3.44	-7.74	0.87	-1.310***	12.89***	6817.88***	-18.85	1562
1995-2000	0.009	3.09	-5.76	0.67	-0.586***	10.49***	3757.49***	-14.13	1565
2001-2006	0.026	8.82	-4.02	0.96	0.9078***	12.76***	6435.02***	41.6	1566
2007-2012	0.075	8.59	-7.55	1.3	-0.110*	7.073***	1085.00***	117.66	1565
2013-2018	-0.03	4.61	-9.81	1.1	-0.788***	9.945***	3308.12***	-21	1565
				Panel B: Metal					
COVID-19	**0.101**	**5.71**	**-5.43**	**1.41**	**-0.36*****	**6.70*****	**160.98*****	**27.34**	**272**
Full-Sample	0.014	8.75	-10.1	1.05	-0.360***	7.665***	17138.7***	116.41	10954
1977-1982	0.085	6.03	-7.46	1.66	-0.219	4.300***	122.981***	133.98	1566
1983-1988	-0.02	7.95	-6.21	1.55	0.094	5.247***	331.836***	-46.46	1565
1989-1994	-0.04	3.42	-6.74	0.92	-0.99***	9.419***	2941.00***	-22.61	1562
1995-2000	-0.05	3.09	-6.23	0.72	-0.47***	9.107***	2491.65***	-8.317	1565
2001-2006	0.027	8.54	-4.23	0.94	0.709***	11.579***	4933.99***	43.287	1566
2007-2012	0.077	8.75	-8.23	1.37	-0.18***	7.015***	1060.54***	121.83	1565
2013-2018	-0.08	5	-10.1	1.18	-0.86***	9.680***	3107.13***	-26.89	1565
				Panel C: Oil					
COVID-19	**-0.05**	**32.01**	**-56.86**	**6.54**	**-2.46*****	**29.02*****	**7948.6*****	**-14.27**	**272**
Full-Sample	0.013	13.57	-38.4	2.15	-0.843***	19.243***	88056.1***	103.04	7823
1989-1994	0.004	13.57	-38.4	2.28	-1.06***	57.97***	199149***	6.64	1562
1995-2000	-0.04	12.23	-11.22	1.76	0.053	6.861***	973.156***	-48.13	1565
2001-2006	0.081	8.072	-16.54	2.26	-0.498***	5.764***	563.068***	128.25	1566
2007-2012	0.047	13.34	-13.06	2.36	-0.175***	6.505***	808.983***	74.343	1565
2013-2018	-0.04	10.14	-10.79	2.09	0.093	5.888***	546.420***	-53.12	1565
				Panel D: Silver					
COVID-19	**0.16**	**7.24**	**-12.35**	**2.83**	**-0.75*****	**6.33*****	**151.19*****	**44.26**	**272**
Full-Sample	0.014	12.47	-19.48	1.79	-0.774***	8.570***	21149.2***	115.15	10954
1977-1982	0.081	7.768	-7.411	1.79	-0.072	4.125***	84.0107***	128.26	1566
1983-1988	-0.07	8.2	-8.801	2.11	-0.089	4.277***	108.479***	-108.2	1565
1989-1994	-0.03	7.658	-12.8	1.57	-0.695***	10.861***	4148.16***	-38.72	1562
1995-2000	0.019	9.236	-9.6	1.58	-0.09	6.878***	982.980***	30.77	1565
2001-2006	0.019	7.466	-11.79	1.39	-0.782***	10.610***	3938.74***	30.891	1566
2007-2012	0.096	12.47	-14.79	2.28	-0.734***	8.597***	2183.97***	150.95	1565
2013-2018	-0.05	7.708	-19.48	2.02	-1.098***	11.139***	4634.86***	-66	1565

Note: *** Indicates significance at 1%. ** Indicates significance at 5%. * Indicates significance at 10%.

Source: Author's explanation of statistical figures from data stream using R-Statistical Package.

where the sample size is represented by n while any two observations possess the maximum difference ε for any embedded dimension m which is calculated during computation of correlational-integrals. The test statistic of the BDS is:

$$W_m(\varepsilon) = \sqrt{\frac{n}{\hat{V}_m}} \left(C_m(n, \varepsilon) - C_1(n, \varepsilon)^m \right) \tag{19}$$

where correlation integrals have a standard deviation of $\hat{V}_m$. With a normal distribution, $\sqrt{n} \left(C_m(n, \varepsilon) - C_1(n, \varepsilon)^m \right)$ is considered as a random variable in BDS test, when n increases use $'e' = 0.5\sigma, 1\sigma, 1.5\sigma \text{ and } 2\sigma$ with a null hypothesis. According to Hsieh (1991) the main cause of denial of H_0 of BDS i.e., $i.i.d.$, is the presence of structural changes in the series of returns.

EMPIRICAL RESULTS

Linear Results

Empirical results of linear tests are presented in Tables 2 and 3. Results of the Autocorrelation test for commodities (gold, metal, oil and silver) are presented in Table 2. It is clear from the table that all four commodities are predictable and the commodity market is inefficient in the full-sample and COVID-19 period as the coefficients are significant at a 1% level of confidence. As far as the sub-sample analysis is concerned,

it is clear from the table that in the first two subsamples (1983-1988 and 1989-1994) the gold index is inefficient as the coefficients are significant at a 1% level of confidence but after the first two subsamples the market becomes efficient in next three consecutive

Table 2 Output of Autocorrelation and Runs econometric test for well-known and commonly traded commodities on CBOE in both full and sub-samples. The lag orders up to 5 for autocorrelation coefficients are presented in columns 2-4 and 6-8. Results for the Runs test are presented in columns 5 and 9. While the very first column offers sample eras.

Sample Period	Autocorrelation test			Runs Test
	1	3	5	Z-value
Panel A: Gold				
COVID-19	**-0.501*****	**0.04*****	**0.028*****	**0.166**
Full-Sample	-0.511***	0.026***	0.026***	6.20***
1983-1988	-0.049***	0.039***	-0.011***	6.26***
1989-1994	-0.056**	-0.013	0.02	2.18**
1995-2000	-0.029	0.027	0.041	0.88
2001-2006	-0.015	-0.026	0.008**	1.84*
2007-2012	0.035	0.031	0.04	1.24
2013-2018	-0.524***	0.003***	0.024***	2.17**
Panel B: Metal				
COVID-19	**-0.521*****	**0.039*****	**0.015*****	**0.409**
Full-Sample	-0.511***	0.026***	0.015***	6.95***
1977-1982	0.029***	0.049***	-0.027***	4.65***
1983-1988	-0.034***	0.039***	-0.014***	4.98***
1989-1994	-0.055***	-0.005	0.012	2.45**
1995-2000	-0.018	0.011	0.033	1.8*
2001-2006	-0.029	-0.035	0.009**	1.3
2007-2012	0.03	0.029	0.037	1.44
2013-2018	-0.042*	0.003	0.02	2.68***
Panel C: Oil				
COVID-19	**-0.485*****	**-0.098*****	**-0.115*****	**-0.360**
Full-Sample	-0.499***	-0.01***	-0.026***	3.05***
1983-1988	N/A	N/A	N/A	N/A
1989-1994	0.032	-0.132***	-0.013***	1.57
1995-2000	-0.002	-0.039**	0.015	-0.31
2001-2006	0.001	0.027	-0.026	1.78*
2007-2012	-0.056**	0.016	-0.065**	1.44
2013-2018	-0.091***	0.013***	-0.039***	2.45**
Panel D: Silver				
COVID-19	**-0.596*****	**-0.034*****	**-0.024*****	**1.102**
Full-Sample	-0.509***	0.025***	0.009***	7.50***
1977-1982	0.156***	0.154***	0.059***	2.43**
1983-1988	-0.522***	0.02***	-0.014***	2.76***
1989-1994	-0.513***	0.045***	0.032***	2.87***
1995-2000	-0.517***	0.014***	0.004***	4.22***
2001-2006	-0.507***	-0.022***	-0.017***	2.99***
2007-2012	-0.01	0.003	0.008	1.57
2013-2018	-0.513***	0.015***	-0.016***	2.73***

Note: *** indicates significance at 1%. ** Indicates significance at 5%. * Indicates significance at 10%.

Source: Author's explanation of statistical figures from data stream using R-Statistical Package.
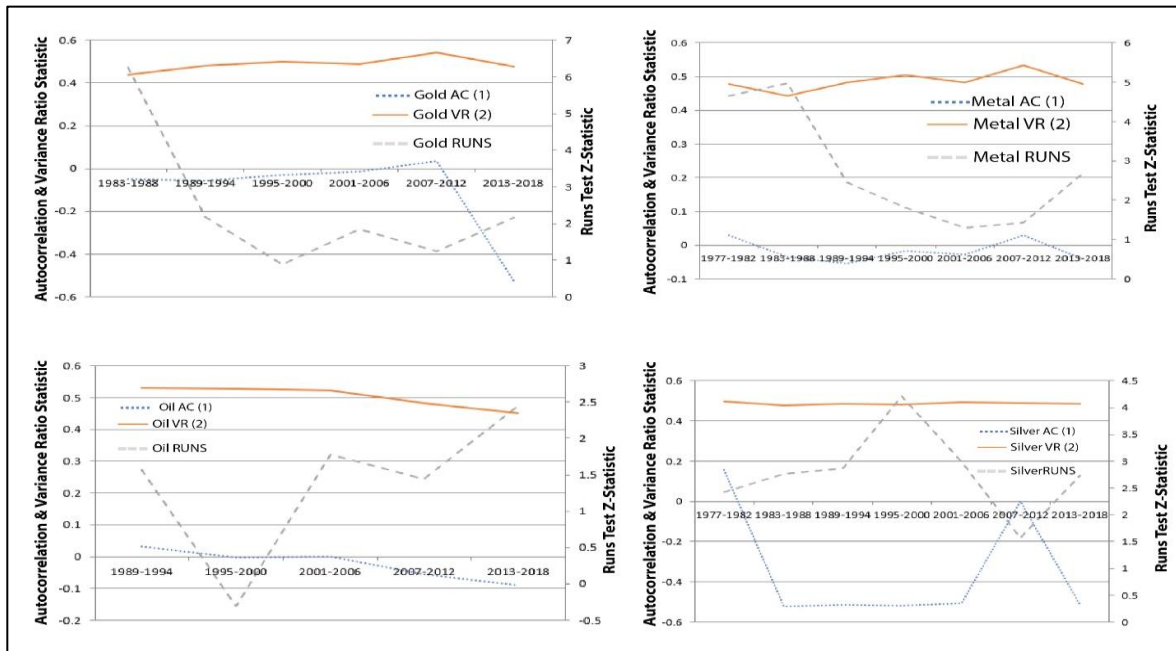
Source: Author's explanation of statistical figures from data stream using R-Statistical Package

Figure 1 Statistics of linear test employed for Commodities (Gold, Metal, Oil and Silver). RUNS stands for z-statistic of the runs test. For lag 1, autocorrelation statistic is represented by AC (1), while, VA (2) stands for the 2-period return of variance ratio test.

Sub-sample comprising years from 1995-2012. The market swings and becomes inefficient as there is significant predictability in the last subsample at a 1% level of confidence. As the returns of the gold index go under the periods of linear predictability and no predictability, thus supporting AMH. Table 2 also shows the autocorrelation results for the metal index. It is clear from the table that returns are predictable (market inefficiency) in the first three sub-samples ranging from the year 1977 to 1994 as the coefficients are significant at a 1 % level of confidence. The behavior of reverses and metal index returns become unpredictable in the rest of the subsamples from 1995 to 2018 indicating market efficiency. The returns of the metal index go under the periods of linear predictability and no predictability, thus supporting AMH.

In the case of the oil index, the results of the autocorrelation test for subsamples show that returns are unpredictable and the market is efficient in the first three sub-samples from the year 1989-2006 (at Lag-1). The behavior of the market then reverses and the market becomes inefficient as the rest of the sub-samples generate significant coefficients/significant predictability. In the case of silver, the sub-samples results show that returns are predictable and the market is inefficient in the sub-samples comprising years from 1977 to 2006 as the returns generate significant coefficients at a 1 % level of confidence. The behavior reverses and the market becomes efficient in the year 2007 to 2012 and returns become unpredictable for investors, but in the last sub-sample (2013-2018) the market again shows predictability of returns hence, market inefficiency. As the returns of both oil and silver indices go under the periods of linear predictability and no predictability, thus supporting AMH.

As for as the results of runs tests are concerned, during the COVID-19 period, the market remains efficient as returns are not predictable as all the Z-values are insignificant. But the Z-values show similar results like the autocorrelations test in the full-sample in all the indices (returns are predictable for all the indices). Similarly, Runs test results are identical to Autocorrelation results in the sub-samples for gold, oil, and silver indices. But the metal returns at runs test show predictability (market inefficiency) in the first three sub-samples ranges from the year 1977 to 1994 as the Z-values are significant at a 1 % level of confidence. The behavior of reverses and metal index returns become unpredictable (market efficiency) in the next three sub-samples (1995-2000, 2001-2006 and 2007-2012). In the last sub-sample (2013-2018) market again becomes inefficient as the Z-value is significant at a 1 % level of confidence.

Table 3 presents the results of the variance ratio test which shows that all the indices gold, metal, oil, and silver generates significant coefficients at a 1% level of confidence for all k's = 8 and 16 in the full sample, during COVID-19 as well as in all sub-samples. This is an indication of linear predictability of returns in all the indices, hence, the market inefficiency. As the returns of the, all the indices go under the periods of linear predictability and no predictability at Autocorrelation and Runs tests, thus supporting AMH, while variance ratio test support market inefficiency of all the commodity indices.

Non-linear Results

Tables 4 and 5 display results for commodities through non-linear empirical tests. The non-linear tests are applied on AR filtered return series and Ljung-Box test statistics are presented in table 3 before and after the implementation of the AR pre-whitening filter. Ljung Box statistic exhibits that temporal linear structure (significant autocorrelation at 1%) exists in full and sub-samples up to 20 lags. So, the AR model is implemented on the returns to remove linear dependence in the series to investigate the non-linear dependence.
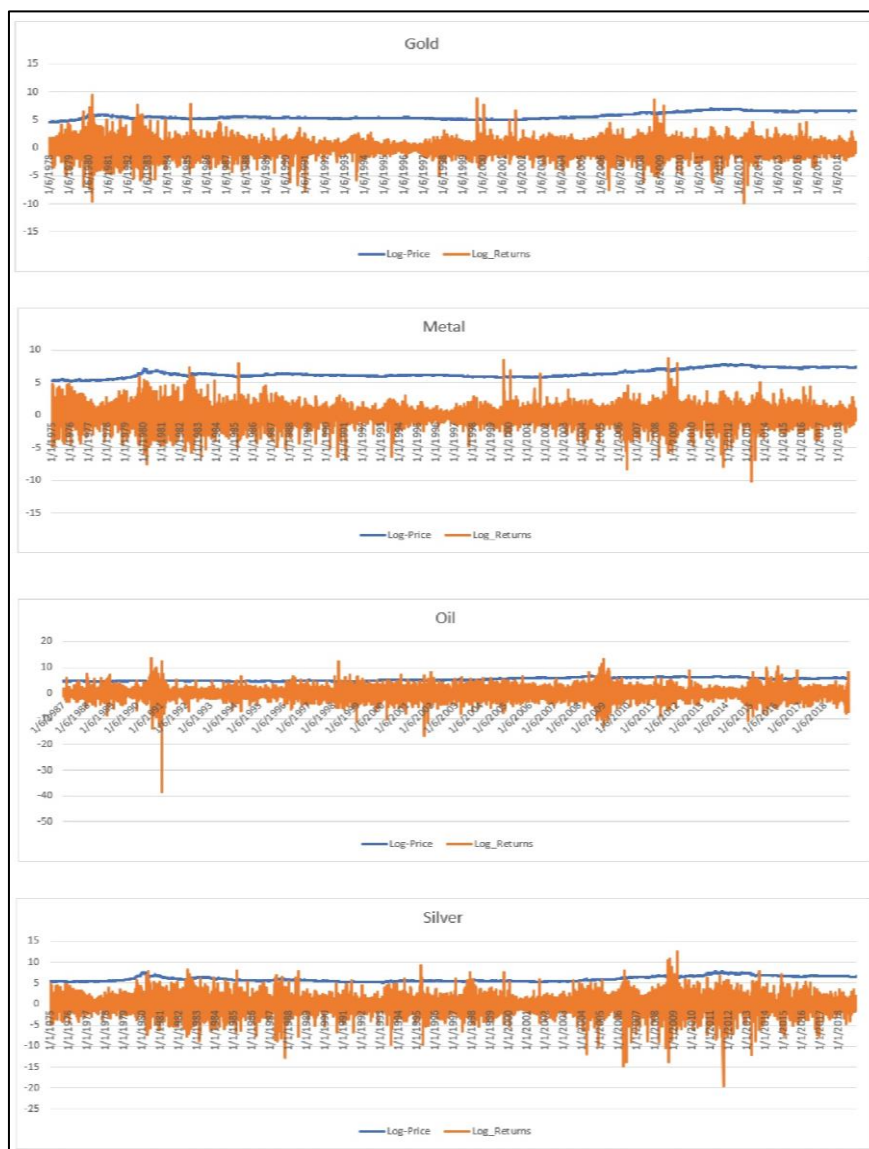
Source: Author's explanation of statistical figures from data stream using R-Statistical Package

Figure 2 Log price and log-returns of Commodities (Gold, Metal, Oil and Silver) over the full-sample period.

Ljung-Box test in columns 4 and 5 of Table 3 shows that there is significant autocorrelation (linear structure) exists in returns of all the commodities in the full as well as in all the sub-samples. Then AR-models are estimated and documented in column 6 of Table 3, which shows that the linear structure is successfully eliminated from the series as the full-sample along with all sub-samples show no statistically significant correlation up to 20 lags at Ljung-Box test (column 7 and 8). To detect non-linear dependency, we subject the filtered returns to non-linear tests (BDS test, Engle LM, McLeod Li test, and Tsay-test) discussed in the methodology. All the nonlinear tests reveal that there exists a significant non-linear dependence in (full-sample and COVID-19 period) up to lag 20 (for Engle LM, McLeod Li, and Tsay tests) and at all the dimensions of the BDS test: indicating that returns from all the commodities remained inefficient over the full sample period.
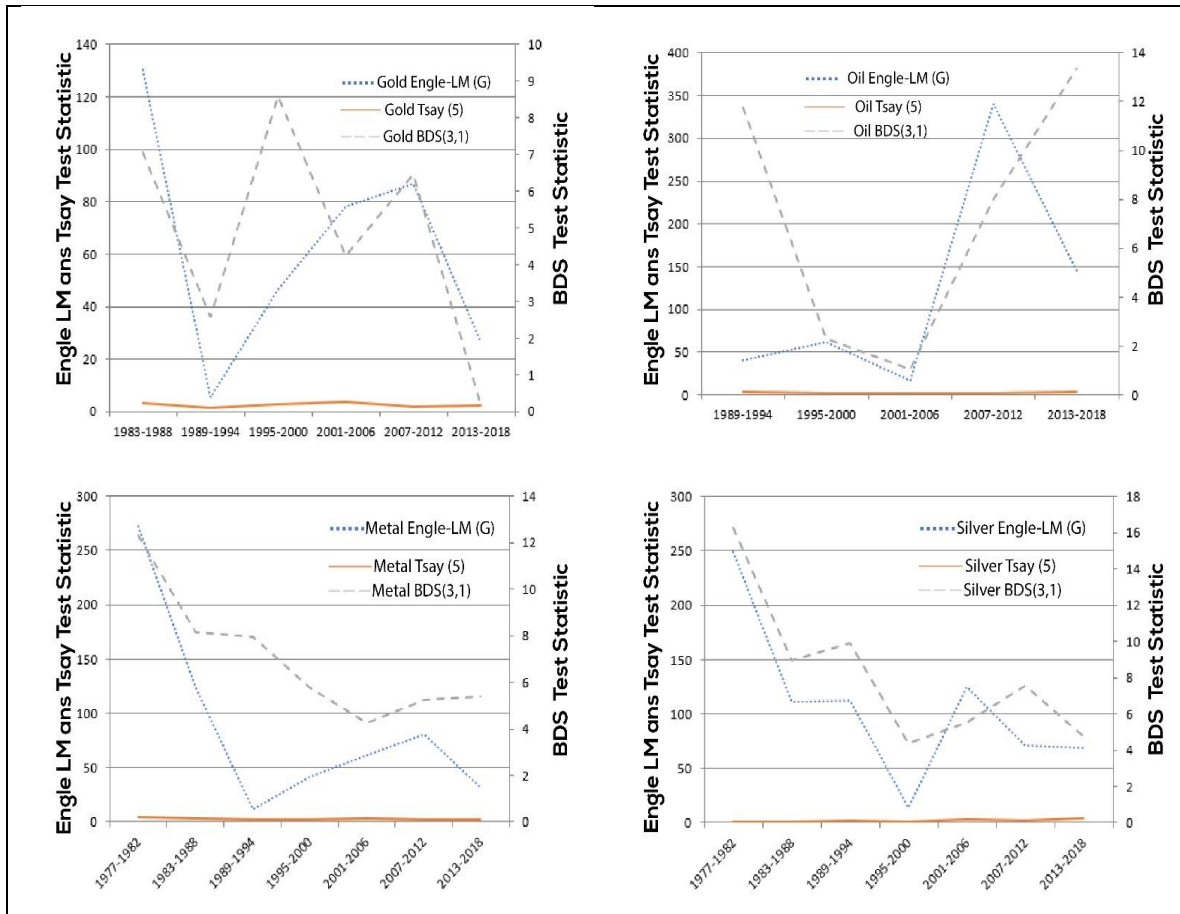
Source: Author's explanation of statistical figures from data stream using R-Statistical Package.

Figure 3 Statistics of non-linear tests employed for Commodities (Gold, Metal, Oil and Silver). BDS (3,1) stands for dimension 3 along with 1σ embedding dimension for BDS test, up to lag 5, LM(5) represents Engle-LM tests statistics, while, Tsay(5) stands return predictability up to lag 5 for Tsay test.

Table 3 Columns 2 and 3 offers output of VR (Variance-ratio) test for k = 4 and 16. LB (Ljung Box) model prior and subsequently fitting "(AR Model Columns 6)" is presented in columns 4-5 and 7-8 respectively for well-known and commonly traded commodities on CBOE in both full and sub-samples. While the very first column offers sample eras.

Sample Period	VR Test		Ljung-Box test Statistic before fitting AR model		AR	Ljung-Box test Statistic after fitting AR model	
	K=4	K=16	Lag10	Lag20		Lag10	Lag20
Panel A: Gold							
COVID-19	**0.287262***	**0.073413***			**4**		
	*	*	**68.787*****	**70.113*****		**0.2188**	**6.772**
Full-Sample	0.243***	0.060***	206.2***	208.9***	1	0.079	21.589
1983-1988	0.250***	0.062***	423.7***	423.7***	5	0.992	11.743
1989-1994	0.236***	0.061***	391.4***	403.4***	5	0.356	19.252
1995-2000	0.251***	0.058***	410.3***	429.5***	4	0.235	15.893
2001-2006	0.227***	0.062***	340.2***	345.6***	5	0.045	8.174
2007-2012	0.258***	0.065***	430.5***	431.0***	5	0.392	14.743
2013-2018	0.241***	0.060***	504.9***	511.0***	4	10.395	0.15
Panel B: Metal							
COVID-19	**0.288343***	**0.071809***			**6**		
	*	*	**74.984*****	**76.496*****		**0.8408**	**8.9987**
Full-Sample	0.257***	0.062***	204.5***	207.4***	8	0.019	7.723
1977-1982	0.266***	0.066***	428.4***	433.4***	3	0.043	17.039
1983-1988	0.254***	0.063***	494.1***	500.3***	8	0.023	5.376
1989-1994	0.238***	0.061***	418.8***	418.9***	9	0.211	16.767
1995-2000	0.255	0.059***	385.8***	393.8***	5	13.928	0.091
2001-2006	0.224***	0.060***	421.9***	442.8***	6	0.06	15.89
2007-2012	0.258***	0.064***	347.2***	352.6***	6	0.088	10.038
2013-2018	0.240***	0.060***	426.7***	427.0***	5	0.257	32.084
Panel C: Oil							
COVID-19	**0.188*****	**0.062**	**64.906*****	**89.409*****	**5**	**2.4329**	**17.786****
Full-Sample	0.254***	0.061***	199.0***	199.3***	9	0.007	6.525
1989-1994	0.257***	0.066***	346.1***	380.5***	3	0.024	15.054
1995-2000	0.252***	0.061***	350.0***	350.1***	10	0.035	14.579
2001-2006	0.252***	0.062***	362.2***	367.5***	7	1.147	34.838
2007-2012	0.231***	0.058***	415.4***	419.1***	1	0.263	12.236
2013-2018	0.230***	0.056***	475.1***	475.3***	10	0.027	11.261
Panel D: Silver							
COVID-19	**0.281064***				**3**		
	*	**0.067587***	**106.89*****	**108*****		**10.482*****	**17.633*****
Full-Sample	0.252***	0.061***	199.0***	200.4***	1	0.08	19.593
1977-1982	0.275***	0.067***	395.9***	402.6***	10	0.0258	7.507
1983-1988	0.265***	0.065***	429.2***	432.1***	9	11.447	0.215
1989-1994	0.248***	0.060***	412.4***	419.4***	1	0.16	20.229
1995-2000	0.254***	0.061***	419.0***	420.8***	1	15.688	0.025
2001-2006	0.237***	0.062***	402.7***	404.7***	2	0.031	9.757
2007-2012	0.257***	0.059***	406.8***	410.1***	3	0.194	8.846
2013-2018	0.238***	0.060***	412.1***	412.4***	1	0.08	10.086

Note: *** Indicates significance at 1%. ** Indicates significance at 5%. *Indicates significance at 10%.

Source: Author's explanation of statistical figures from data stream using R-Statistical Package.

Table 4 presents the results of the Engle LM test, the McLeod Li test, and the Tsay-test. As for as sub-sample analysis is concerned, the gold index is predictable in the first sub-sample (1983-1988) and becomes efficient in the next sub-sample (1989-1994) as the returns are unpredictable with all three tests. The Gold Index is then again predictable in the rest of the subsamples from 1995-2018 as all the sub-samples generate significant coefficients at a 1% level of confidence. This behavior shows that the gold index is fluctuating between non-linear predictability and unpredictability at tests (Engle LM, McLeod Li test, and Tsay-test) thus supporting AMH. In the case of Metal and oil indices, returns are predictable at all three tests in the full as well as in all subsample periods from 1977-2018, thus contradicting EMH. For the Silver index, returns in all the subsamples are predictable at Engle LM and McLeod Li test except the TSAY test where returns are unpredictable in sub-sample (1995-2000), thus silver index support AMH at Tsay test as the returns go under the episodes of significant predictability and unpredictability. As for as the results of the BDS test are concerned the returns of all four indices are predictable (having nonlinear dependence/market inefficiency) in the full sample at both dimensions (3 and 5 dimensions are mostly recommended in the literature). In the sub-sample, the gold returns have nonlinear dependence in all the sub-samples except the last subsample from 2013-2018 which exhibits

unpredictability (no nonlinear dependency/market efficiency) in dimension 3, while in dimension 5 returns are predictable.
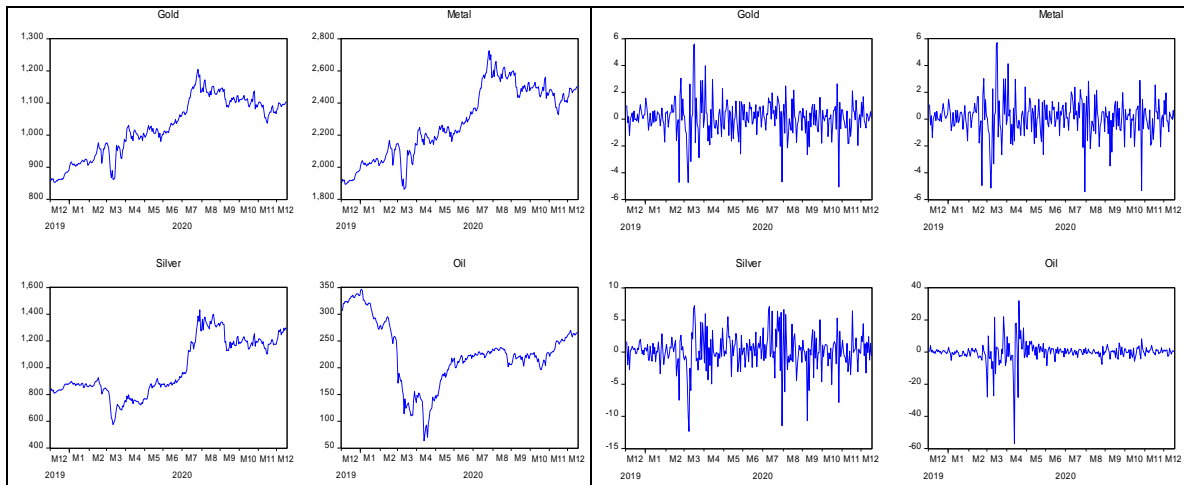

Figure 4 Behavior of prices and returns from commodities during the COVID-19 period. Prices are shown on the left-hand side, while returns are displayed on the right-hand side.

Returns from Oil in the subsamples 1989-1994 and 1995-2000 are predictable but in the next subsample period 2001-2006, returns are unpredictable (market efficiency/no nonlinear predictability) only in dimension 3 and then again predictable at dimension 5. Finally, in the rest of the subsamples from 2007-2018, the oil returns have a nonlinear dependency. As the gold and oil go under the periods of nonlinear predictability and no nonlinear predictability thus supporting AMH. The returns from Metal and silver exhibit nonlinear dependency in all the sub-samples at both dimensions, thus contradicting EMH hence market inefficiency. Figures 1 and 3 are evidence of varying behavior of commodities as the coefficients of all the tests fluctuate over time.

Table 4 Output of Engle-LM and Tsay econometric Models for well-known and commonly traded commodities on CBOE in both full and sub-samples are presented in columns 3-4 and 5-6 respectively. The lag orders up to 10 and 20 are presented for each test for returns filtered by the AR model. While the output of the McLeod-Li test model is presented in columns 7-8 for Qrr up to 20 to testify the i.i.d processes, where "I" signifies the independence of returns, and "D" signifies the dependence of returns from commodities. While the very first column offers sample eras.

Sample-Period	AR	Engle LM Test-Statistic		TSAY Test-Statistic		McLeod-Li Test-Statistic	
		Lag10	Lag20	Lag10	Lag20	Qrr(10)	Qrr(20)
Panel A: Gold							
COVID-19	**4**	**59.7*****	**88.3*****	**1.23*****	**1.59*****	**D**	**D**
Full-Sample	1	1466.2***	1525***	6.12***	4.30***	D	D
1983-1988	5	143.1***	171.9***	2.10***	1.84***	D	D
1989-1994	5	19.42	27.57	1.63***	1.50***	D	D
1995-2000	4	52.3***	62.4***	2.50***	1.61***	D	D
2001-2006	5	79.8***	86.6***	1.96***	1.27***	D	D
2007-2012	5	100.1***	144.7***	1.78***	2.13***	D	D
2013-2018	4	32.6***	39.8***	1.96***	1.52***	D	D
Panel B: Metal							
COVID-19	**6**	**70.9*****	**79.4*****	**1.53*****	**1.36*****	**D**	**D**
Full-Sample	8	1118.2***	1186***	4.17***	3.45***	D	D
1977-1982	3	289.8***	296.5***	3.04***	2.48***	D	D
1983-1988	8	137.6***	167.8***	1.93***	1.69***	D	D
1989-1994	9	31.4***	37.1***	1.89***	1.66***	D	D
1995-2000	5	45.6***	54.5***	1.99***	1.42***	D	D
2001-2006	6	62.7***	69.2***	1.71***	1.25***	D	I
2007-2012	6	94.6***	134.2***	1.80***	2.01***	D	D
2013-2018	5	37.6***	43.5***	1.87***	1.42***	D	D
Panel C: Oil							
COVID-19	**5**	**32.5*****	**37.5**	**1.59*****	**1.17*****	**D**	**D**
Full-Sample	9	313.6***	346.2***	3.50***	3.12***	D	D
1989-1994	3	50.4***	51.7***	6.49***	4.67***	D	D
1995-2000	10	62.9***	89.0***	1.51***	1.42***	D	D
2001-2006	7	22.6***	24.5	1.69***	1.28***	D	D
2007-2012	1	386.3***	455.2***	2.94***	3.35***	D	D
2013-2018	10	175.6***	195.3***	3.04***	2.31***	D	D
Panel D: Silver							
COVID-19	**3**	**123.0*****	**154.9*****	**2.43*****	**2.36*****	**D**	**D**
Full-Sample	1	771.7***	865.4***	2.56***	2.67***	D	D
1977-1982	10	268.4***	289.7***	2.03***	2.09***	D	D
1983-1988	9	133.4***	154.9***	1.74***	1.56***	D	D
1989-1994	1	146***	176.0***	3.45***	3.07***	D	D
1995-2000	1	20.1***	37.8***	1.049	1.38***	D	D
2001-2006	2	146.1***	158.8***	2.43***	2.07***	D	D
2007-2012	3	109.0***	135.9***	2.24***	2.21***	D	D
2013-2018	1	75.1***	78.4***	2.06***	1.69***	D	D

Note: *** Indicates significance at 1%. ** Indicates significance at 5%. * Indicates significance at 10%.

Source: Author's explanation of statistical figures from data stream using R-Statistical Package.

Table 5 Output of BDS econometric model fitted on residuals of returns obtained by AR filter for well-known and commonly traded commodities on CBOE in both full and sub-samples. Row 1 presents dimensions while row 2 presents embedded dimensions to the extent of the standard deviation of the data series. While very first column offers sample eras.

Dimensions		3		5	
Embedded dimensions	AR	1σ	2σ	1σ	2σ
Sample-Period					
Panel A: Gold					
COVID-19	**4**	**1.723094***	**3.178096*****	**4.747398*****	**5.066136*****
Full-Sample	1	22.30***	25.87***	30.48***	29.93***
1983-1988	5	7.06***	7.15***	8.05***	8.11***
1989-1994	5	2.58***	1.4265	4.06***	2.69***
1995-2000	4	8.58***	4.63***	12.91***	7.40***
2001-2006	5	4.22***	3.81***	4.91***	4.29***
2007-2012	5	6.47***	6.88***	8.59***	8.89***
2013-2018	4	0.1776	2.77***	2.21***	4.28***
Panel B: Metal					
COVID-19	**6**	**1.321173**	**2.798747*****	**4.321174*****	**4.636505*****
Full-Sample	8	21.82***	24.08***	30.64***	28.98***
1977-1982	3	12.30***	13.69***	8.976***	11.59***
1983-1988	8	8.17***	7.72***	6.85***	6.196***
1989-1994	9	7.95***	7.01***	10.509***	9.149***
1995-2000	5	5.78***	6.60***	7.212***	6.84***
2001-2006	6	4.228***	5.81***	5.918**	4.29***
2007-2012	6	5.22***	5.81***	5.918***	5.29***
2013-2018	5	5.376***	4.940***	6.958***	6.147***
Panel C: Oil					
COVID-19	**5**	**8.559934*****	**9.32833*****	**11.21292*****	**12.33117*****
Full-Sample	9	24.81***	24.04***	32.24***	27.90***
1989-1994	3	11.78***	11.76***	16.47***	13.97***
1995-2000	10	2.32**	1.79*	3.98***	3.30***
2001-2006	7	1.0524	2.49**	1.77***	3.25***
2007-2012	1	8.01***	12.65***	9.79***	16.02***
2013-2018	10	13.33***	10.54***	18.91***	13.73***
Panel D: Silver					
COVID-19	**3**	**2.958229*****	**4.232766*****	**5.453803*****	**5.648736*****
Full-Sample	1	16.55***	20.14***	23.40***	24.96***
1977-1982	10	16.25***	13.64***	21.53***	16.83***
1983-1988	9	8.95***	8.01***	10.50***	9.14***
1989-1994	1	9.89***	8.87***	11.55***	10.14***
1995-2000	1	4.37***	3.94***	5.95***	5.14***
2001-2006	2	5.56***	6.27***	8.39***	7.88***
2007-2012	3	7.56***	8.82***	9.10***	10.36***
2013-2018	1	4.78***	5.60***	6.21***	5.84***

Note: *** Indicates significance at 1%. ** Indicates significance at 5%. * Indicates significance at 10%.

Source: Author's explanation of statistical figures from data stream using R-Statistical Package.

CONCLUSION

In this article, we have examined the time-varying efficiency through AMH (Adaptive Market Hypothesis) of four internationally traded commodities which induce that profit opportunity to arise from time to time. With the application of a battery of linear and nonlinear empirical tests, we find linear and nonlinear serial dependence in a series of returns. The autocorrelation and runs tests show that all the indices go under the episodes of linear predictability (market inefficiency) and no linear predictability (market efficiency), thus supporting AMH. The variance ratio test shows that the commodity returns remain predictable in full and all the subsamples hence, market inefficiency. As for as the results of the nonlinear tests are concerned, Metal and Oil returns have nonlinear dependency (market inefficiency/predictability) in all the sub-samples with Engle LM, McLeod Li and Tsay tests, hence market inefficiency. Gold index returns with Engle LM, McLeod Li and Tsay tests, and silver index returns with only Tsay test go under the periods of nonlinear dependence and no nonlinear dependence thus supporting AMH. Similarly, at BDS test Gold and oil indices pass through the periods of predictability and no predictability and support AMH, while metal and silver indices have nonlinear dependence throughout. We, therefore, conclude, that the commodity indices go under the episodes of nonlinear dependence and no nonlinear dependence thus supporting AMH. Therefore, we conclude that the

Adaptive Market Hypothesis (AMH) is a better description of the behavior of commodity indices than traditional EMH. The results of our study are consistent with the findings of (Urquhart and Hudson, 2013; Hiremath and Kumari, 2014; Ramirez et al., 2015; Noda, 2016; Shahid et al., 2019). On the other hand, returns from all the commodities are highly volatile and predictable during COVID-19, as all the tests are evidence of the presence of linear and non-linear predictability of returns. The research helps academicians/authors/researchers to understand the theoretical and practical aspects of the stock market and its behavior as well. The results of the study are helpful for individual investors as well as portfolio managers and brokers to make appropriate strategies to forecast the prices of commodities.

We believe that a sub-sample analysis of a long period may be more appropriate to explain the idea of market adaptability. Furthermore, the current methodology can be applied to other commodity markets of the world, stock markets, and currency markets. Furthermore, a study on the investigation of several significant windows for these commodities in economic/political/social triggers would also be interesting, but we rest it for future studies.

REFERENCES

Adrangi, B. and Chatrath, A., 2003. Non-linear Dynamics in Futures Prices: Evidence from the Coffee, Sugar, and Cocoa Exchange. *Applied Financial Economics*, *12*(4), pp.245-256.

Ahti, V., 2009. Forecasting Commodity Prices with nonlinear Models.

Alharbi, A. M., 2009. *Nonlinearity and Market Efficiency in GCC Stock Markets.* Doctoral Thesis.

Ali, M., Alam, N. and Rizvi, S. A. R., 2020. Coronavirus (COVID-19)–An epidemic or pandemic for financial markets. *Journal of Behavioral and Experimental Finance*, p.100341.

Al-Awadhi, A. M., Al-Saifi, K., Al-Awadhi, A. and Alhamadi, S., 2020. Death and contagious infectious diseases: Impact of the COVID-19 virus on stock market returns. *Journal of Behavioral and Experimental Finance*, p.100326. https://doi.org/10.1016/j.jbef.2020.100326

Al-Khazali, O. M., Ding, D. K. and Pyon, C. S., 2007. A New Variance Ratio Test of Random Walk in Emerging Markets: A Revisit. *The Financial Review*, *42*(2), pp.303-317. https://doi.org/10.1111/j.1540-6288.2007.00173.x

Alrabadi, D.-W. H. and Al-Qudah, K. A., 2012. Calendar Anomalies: The Case of Amman Stock Exchange. *International Journal of Business and Management*, *7*(24), pp.120-127. https://doi.org/10.5539/ijbm.v7n24p120

Alvarez-Ramirez, J., Rodriguez, E. and Eapinosa-Paredes, G., 2012. Is the US stock Market Becoming weakly Efficient over Time? Evidence from 80-year-Long Data. *Physica A: Statistical Mechanics and its Applications*, *391*(22), pp.5643-5647. https://doi.org/10.1016/j.physa.2012.06.051

Amini, S., Hudson, R. and Keasey, K., 2010. Stock return predictability despite low autocorrelation. *Economics Letters*, *108*(1), pp.101-103. https://doi.org/10.1016/j.econlet.2010.04.031

Arouri, M., Jouini, J. and Nguyen, D., 2013. On the relationship between world oil prices and GCC stock markets. *Journal of Quantitative Economics*, *10*.

Ashraf, B. N., 2020. Stock markets' reaction to COVID-19: cases or Fatalities?. *Research in International Business and Finance*, p.101249. https://doi.org/10.1016/j.ribaf.2020.101249

Basir, T., Ilyas, M. and Ayesha, F., 2011. Testing the Weak-Form Efficiency of Pakistani Stock Markets- An Empirical Study in the Banking Sector. *European Journal of Economics, Finance & Administrative Sciences*, *31*, pp.160-175.

Batten, J. Ciner, C. and Lucey, B., 2008. The Macroeconomic Determinants of Volatility in Precious Metals Markets. *Resources Policy*, *35*, pp.65-71. https://doi.org/10.1016/j.resourpol.2009.12.002

Baur, D., 2013. The structure and degree of dependence: A quantile regression approach. *Journal of Banking & Finance*, *37*(3), pp.786-798. https://doi.org/10.1016/j.jbankfin.2012.10.015

Baur, D. and McDermott, T., 2010. Is gold a safe haven? International evidence. *Journal of Banking & Finance*, *34*(8), pp.1886-1898. https://doi.org/10.1016/j.jbankfin.2009.12.008

Benavides, G., 2004. Price Volatility Forecasts for Agricultural Commodities: An Application of Historical volatility models, option-implied, and composite approaches for futures prices of corn and wheat. *Journal of Management, Finance, and Economics*, *3*(2), pp.40-59.

Blank, S. C., 1991. Chaos" in Futures Markets? A Nonlinear Dynamical Analysis. *Journal of Futures Markets*, *11*(6), pp.711-728.

Bollerslev, T., 1986. Generalized Autoregressive Conditional Heteroskedasticity. *Journal of Econometrics*, pp.307-327. https://doi.org/10.1016/0304-4076(86)90063-1

Brock, W. A., Hsieh, D. A. and LeBaron, B., 1991. Nonlinear Dynamics, Chaos, and Instability: Statistical Theory and Economic Evidence. Cambridge, Ed.

Brock, W. A., Scheinkman, J. A., LeBaron, B. and Dechert, W. D., 1996. A Test for Independence Based on the Correlation Dimention. *Econometric Reviews*, *15*(3), pp.197-235.

Brooks, C. and Henry, O. T., 2000. Can Portmanteau Nonlinearity Tests Serve as General Mis-Specification Tests? Evidence from Symmetric and Asymmetric GARCH Models. *Economics Letters*, *67*, pp.245-251.

Campbell, J. Y., Lo, A. W. and Mackinlay, A. C., 1997. *The Econometrics of Financial Markets.* N. Princeton, Ed. Princeton University Press.

Chakraborty, M., 2006. Market Efficiency for the Pakistan Stock Market. *South Asia Economic Journal*, *7*(1), pp.67-81. https://doi.org/10.1177/139156140500700104

Charles, A. and Darne, O., 2009. Variance-Ratio Tests of Random Walk: An Overview. *Journal of Economic Surveys*, *23*(3), pp.503-527. https://doi.org/10.1111/j.1467-6419.2008.00570.x

Charles, A., Darne, O. and Kim, J. H., 2012. Exchange-Rate Predictability and Adaptive Market Hypothesis: Evidence from Major Exchange Rates. *Journal of International Money and Finance*, *31*(6), pp.1607-1626. https://doi.org/10.1016/j.jimonfin.2012.03.003

Choi, I., 1999. Testing the Random Walk Hypothesis for Real Exchange Rates. *Journal of Applied Econometrics*, *14*(3), pp.293-308. https://doi.org/10.1002/(sici)1099-1255(199905/06)14:3<293::aid-jae503>3.3.co;2-x

Ciner, C., Gurdgiev, C. and Lucey, B., 2013. Hedges and safe havens: An examination of stocks, bonds, gold, oil and exchange rates. *International Review of Financial Analysis*, *29*(c), p.202-211. https://doi.org/10.1016/j.irfa.2012.12.001

Daskalaki, C. and Skiadopoulos, G., 2011. Should investors include commodities in their portfolios after all? New evidence. *Journal of Banking & Finance*, *35*(10), pp.2606-2626. https://doi.org/10.1016/j.jbankfin.2011.02.022

Dunford, D., Dale, B., Stylianou, N., Lowther, E., Ahmed, M. and De la Torres Arenas, I., 2020. Coronavirus: The world in lockdown in maps and charts. *BBC News,[S. l.].*

Engle, R. F., 1982. Autoregressive Conditional Heteroskedasticity with Estimates of the Variance of United Kingdom Inflation. *Econometrica*, *50*(4), pp.987-1008.

Eswara, M., 2015. An Empirical Study on Performance of Gold ETFs in India - Post Crash Period. SSRN Electronic Journal. 10.2139/ssrn.2679686.

Fama, E. F. and French, K. R., 1988. Permanent and Temporary Components of Stock Prices. *The Journal of Political Economy*, *96*(2), pp. 246–273. https://doi.org/10.1086/261535

Fama, F. E., 1970. Efficient Capital Markets: A review of Theory and Empirical Work. *Journal of Finance*, *25*(2), pp.383-417. https://doi.org/10.2307/2325486

Gates, B., 2020. Responding to Covid-19—a once-in-a-century pandemic?. *New England Journal of Medicine*, *382*(18), pp.1677-1679.

Ghazani, M. M. and Araghi, M. K., 2014. Evaluation of the Adaptive Market Hypothesis as an Evolutionary Perspective on Market Efficiency: Evidence from the Tehran Stock Exchange. *Research in International Business and Finance*, *32*, pp.50-59.

Granger, C. J. and Andersen, A. P., 1978. *An Introduction to Bilinear Time Series Models.* Gottingen : Vandenhoeck & Ruprecht.

Grassberger, P. and Proceaccia, I., 1983. Measuring the Strangeness of Strange Attractors. *Physica: Nonlinear Phenomena*, *9*(1-2), pp.189-208.

Gunay, S., 2021. Comparing COVID-19 with the GFC: A shockwave analysis of currency markets. *Research in International Business and Finance*, *56*, p.101377. https://doi.org/10.1016/j.ribaf.2020.101377

He, C., Jiang, C. and Molyboga, M., 2019. Risk premia in Chinese commodity markets. *Journal of Commodity Markets*, *15*, p.100075. https://doi.org/10.1016/j.jcomm.2018.09.003

Hiremath, G. S. and Kumari, J., 2014. Stock Returns Predictability and the Adaptive Market Hypothesis in Emerging Markets: Evidence from India. *Springer Plus*, pp.3-14. https://doi.org/10.1186/2193-1801-3-428

Hoque, H. A., Kim, J. H. and Pyun, C. S., 2007. A Comparison of Variance Ratio Tests of Random Walk: A Case of Asian Emerging Stock Markets. *International Review of Economics & Finance*, *16*(4), pp.488-502. https://doi.org/10.1016/j.iref.2006.01.001

Hsieh, D. A., 1989. Testing for Nonlinearity in Daily Foreign Exchange Rate Changes. *Journal of Business*, *63*(3), pp.339-368.

Hsieh, D. A., 1991. Chaos and Nonlinear Dynamics: Application to Financial Markets. *The Journal of Finance, 46*(5), pp.1839-1877. https://doi.org/10.1111/j.1540-6261.1991.tb04646.x

Ito, M. and Sugiyama, S., 2009. Measuring the Degree of Time-Varying Market Inefficiency. *Economics Letters*, *103*(1), pp.62-64.

Jegadeesh, N. and Titman, S., 1993. Returns to Buying Winners and Selling Losers: Implications for Stock Market Efficiency. *The Journal of Finance*, *48*(1), pp.65-91. https://doi.org/10.1111/j.1540-6261.1993.tb04702.x

Keenan, D. M., 1985. A Tukey Nonadditivity-type Test for Time Series Nonlinearity. *Biometrika*, *72*(1), pp.39-44. https://doi.org/10.2307/2336333

Kim, J. H. and Shamsuddin, A., 2008. Are Asian Stock Markets Efficient? Evidence from the new Multiple Variance Ratio Test. *Journal of Empirical Finance*, *15*(3), pp.518-532. https://doi.org/10.1016/j.jempfin.2007.07.001

Kim, J. H., Shamsuddin, A. and Lim, K. P., 2011. Stock Return Predictability and the Adaptive Market Hypothesis: Evidence from Century Long US data. *Journal of Empirical Finance*, *18*(5), pp.868-879.

Li, Z., Ge, J., Yang, M., Feng, J., Qiao, M., Jiang, R., ... and Zhou, Q., 2020. Vicarious traumatization in the general public, members, and non-members of medical teams aiding in COVID-19 control. *Brain, behavior, and immunity*.

Lim, K. P., Brooks, R. D. and Hinich, M. J., 2008. Nonlinear Serial Dependence and the Weak-Form Efficiency of Asian Emerging Markets. *Journal of International Financial Markets, Institutions, and Money*, *18*(5), pp.527-544. https://doi.org/10.1016/j.intfin.2007.08.001

Lim, K. P., Luo, W. and Kim, J., 2013. Are US Stock Index Returns Predictable? Evidence from Automatic Autocorrelation-Based Tests. *Applied Economics*, *45*(8), pp.953-962. https://doi.org/10.1080/00036846.2011.613782

Lim, K.-p. and Hooy, C.-W., 2013. Non-linear predictability in G7 stock index returns. *The Manchester School*, *81*(4), pp.620-637. https://doi.org/10.1111/j.1467-9957.2012.02303.x

Liu, H., Manzoor, A., Wang, C., Zhang, L. and Manzoor, Z., 2020. The COVID-19 outbreak and affected countries stock markets response. *International Journal of Environmental Research and Public Health*, *17*(8), p.2800. https://doi.org/10.3390/ijerph17082800

Ljung, M. G. and Box, E. G., 1978. On a Measure of a Lack of Fit in Time Series Models. *Biometrika*, *65*(2), pp.297-303. https://doi.org/10.1093/biomet/65.2.297

Lo, A. W., 2004. The Adaptive Market Hypothesis. *Journal of Portfolio Management*, *30*, pp.15-29. https://doi.org/10.3905/jpm.2004.442611

Lo, A. W., 2005. Reconciling Efficient Market with Behavioral Finance: The Adaptive Market Hypothesis. *Journal of Investment Consulting*, *7*(2), pp.21-44.

Lo, A. W. and MacKinlay, C. A., 1988. Stock Market Prices do not Follow Random Walks: Evidence from a Simple Specification Test. *The Review of Financial Studies*, *1*(1), pp.41-66. https://doi.org/10.1093/rfs/1.1.41

Lucey, B. and Li, S., 2015, What precious metals act as safe havens, and when? Some US evidence, *Applied Economics Letters*, *22*(1), pp.35-45. https://doi.org/10.1080/13504851.2014.920471

McLeod, A. I. and Li, W. K., 1983. Diagnostic checking ARMA time series models using squared-residual autocorrelations. *Journal of Time Series Analysis*, *4*, pp.269-273. https://doi.org/10.1111/j.1467-9892.1983.tb00373.x

Neely, C. J., Weller, P. A. and Ulrich, J. M., 2009. The Adaptive Markets Hypothesis: Evidence from the Foreign Exchange Market. *Journal of Financial and Quantitative Analysis*, *44* (2), pp.467-488. https://doi.org/10.1017/s0022109009090103

Noda, A., 2012. A Test of the Adaptive Market Hypothesis using the Non-Bayesian Time-Varying AR Model in Japan. *Financial Research Letter*.

Noda, A., 2016. A test of Adaptive Market Hypothesis Using a Time-Varying AR Model in Japan. *Finance Research Letters*, *17*, pp.66-71. https://doi.org/10.1016/j.frl.2016.01.004

Ntim, C., Lindop, S., Osei, K. and Thomas, D., 2013. Executive Compensation, Corporate Governance and Corporate Performance: A Simultaneous Equation Approach. *Managerial and Decision Economics*, *36*(2), pp. 67–96. https://doi.org/10.1002/mde.2653

Onali, E., 2020. Covid-19 and stock market volatility. *Available at SSRN 3571453*.

Papadamou, S., Fassas, A., Kenourgios, D. and Dimitriou, D., 2020. Direct and Indirect Effects of COVID-19 Pandemic on Implied Stock Market Volatility: Evidence from Panel Data Analysis.

Pierdzioch, C., Risse, M. and Rohloff, S., 2014. On the Efficiency of the Gold Market: Results of a Real-Time Forecasting Approach. *International Review of Financial Analysis*, 32, pp. 95–108. https://doi.org/10.1016/j.irfa.2014.01.012

Poshakwale, S., 1996. Evidence on Weak Form Efficiency and Day of The Week Effect in the Indian Stock Market. *Finance India*, *X*(3), pp.605-616.

Ramirez, S. C., Arellano, P. L. and Rojas, O., 2015. Adaptive Market Efficiency of Agricultural Commodity Future Contracts. *Contraduria Administracion*, *60*, pp.389-401.

Ramirez, S. C., Grajed, M. R. and Arellano, P. L.-C., 2014. Inefficiency in the international coffee market: The case of Colombian Arabica. *African Journal of Agricultural Research*, *9*(5), pp.556-561.

Shahid, M. N. and Sattar, A., 2017. Behavior of Calendar Anomalies, Market Conditions and Adaptive Market Hypothesis: Evidence from Pakistan Stock Exchange. *Pakistan Journal of Commerce and Social Sciences*, *11*(2), pp.471-504.

Shahid, M. N., Coronado, S. and Sattar, A., 2019a. Stock market behaviour: efficient or adaptive? Evidence from the Pakistan Stock Exchange. *Afro-Asian Journal of Finance and Accounting*, *9*(2), pp.167-192.

Shahid, M. N., Jehanzeb, M., Abbas, A., Zubair, A. and Akbar, M. A. H., 2019b. Predictability of precious metals and adaptive market hypothesis. *International Journal of Emerging Markets*, *15*(5), pp. 1011–1027. https://doi.org/10.1108/ijoem-07-2018-0404

Shahid, M. N., Latif, K., Chaudhary, G. M. and Adil, S., 2020. Financial Crises and Adaptive Market Hypothesis: An Evidence from International Commodities traded at New York Stock Exchange. *Review of Economics and Development Studies*, *6*(1), pp.67-81. https://doi.org/10.47067/reads.v6i1.185

Siegel, S., 1956. *Nonparametric Statistics for the Behavioural Sciences.* New York: McGraw-Hill.

Silvennoinen, A. and Thorp, S., 2013. Financialization, crisis and commodity correlation dynamics. *Journal of International Financial Markets, Institutions and Money*, *24*(c), pp.42-65. https://doi.org/10.1016/j.intfin.2012.11.007

Smith, G., 2012. The Changing and Relative Efficiency of European Emerging Stock Markets. *European Journal of Finance*, *18*(8), pp.689-708. https://doi.org/10.1080/1351847x.2011.628682

Smith, G. and Ryoo, H. J., 2003. Variance Ratio Tests of the Random Walk Hypothesis for European Emerging Stock Markets. *The European Journal of Finance*, *9*, pp.290-300. https://doi.org/10.1080/1351847021000025777

Solt, M. E. and Swanson, P. J., 1981. On the Efficiency of the Markets for Gold and Silver. *The Journal of Business*, *54*(3), pp.453-78. https://doi.org/10.1086/296140

Tansuchat, R., Chang, C.-L. and McAleer, M., 2009. Modeling Long Memory Volatility in Agricultural Commodity Future Returns. *CARF-F-183 Series, Center for Advanced Research in Finance. Faculty of Economics, University of Tokyo*.

Tang, K. and Xiong, W., 2012. Index Investment and the Financialization of Commodities. *Financial Analysts Journal*, *68*(6), pp.54-74. https://doi.org/10.2469/faj.v68.n6.5

Tejeda, H. A. and Goodwin, B. K., 2009. Price Volatility, Nonlinearity, and Asymmetric Adjustments in Corn, Soybean, and Cattle Markets: Implication of Ethanol-Driven (Markets) Shocks. *In the NCCC-134 Conference on Applied Commodity Price Analysis, Forecasting, and Market Risk Management.* St. Louis: Missouri.

Tsay, R. S., 1986. Nonlinearity tests for time series. *Biom*, *73*, pp.461–466.

Urquhart, A., 2013. An Empirical Analysis of the Adaptive Market Hypothesis and Investor Sentiment in Extreme Circumstances. *Ph.D. Thesis*.

Urquhart, A. and Hudson, R., 2013. Efficient or Adaptive Markets? Evidence from Major Stock Markets using very Long-Run Historic Data. *International Review of Financial Analysis*, *28*, pp.130-142.

Urquhart, A., 2017. How predictable are precious metal returns?. *The European journal of finance*, *23*(14), pp.1390-1413. https://doi.org/10.1080/1351847x.2016.1204334

Vivian, A. and Wohar, M., 2012. Commodity volatility breaks. *Journal of International Financial Markets, Institutions and Mon*ey, *22*(2), pp.395-422. https://doi.org/10.1016/j.intfin.2011.12.003

Wright, J. H., 2000. Alternative Variance-Ratio Tests Using Ranks and Signs. *Journal of Business & Economic Statistics*, *18*(1), pp.1-9. https://doi.org/10.1080/07350015.2000.10524842

Yang, S.-R. and Brosen, W. B., 1993. Nonlinear Dynamics of daily futures prices: Conditional Heteroskedasticity or Chaos. *Journal of Futures Markets*, *13*(2), pp.175-191.