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

MUHAMMAD NAEEM SHAHID\textsuperscript{a*}, MUHAMMAD UMAR ISLAM\textsuperscript{b}, NAFIS ALAM\textsuperscript{b} AND MOHSIN ALI\textsuperscript{c}

\textsuperscript{a}Government College University Faisalabad, Chiniot Campus, Pakistan
\textsuperscript{b}Asia Pacific University of Technology and Innovation, Malaysia
\textsuperscript{c}Taylors University, Malaysia

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.

JEL Classification: G4, G41
Keywords: Adaptive Market Hypothesis; Efficient Market Hypothesis; Commodities; Linear Prediction; Nonlinear Prediction

\footnote{Article history:
Received: 29 September 2021
Accepted: 20 March 2022

* Corresponding author: Email: naeemtuf@gmail.com
DOI: http://doi.org/10.47836/ijeamsi.16.1.005
© International Journal of Economics and Management. ISSN 1823-836X. e-ISSN 2600-9390.}
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.

Auto-regressive (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,
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 2009). However, we test for both linearity and non-linearity in full as well as sub-samples to integrate the idea of AMH.
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. Pierdziach 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 1st, 1989 to December 31st, 2018, for the gold index from January 1st, 1983 to December 31st, 2018, for silver and metal indices from January 1st, 1977 to December 31st, 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:

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

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 of 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 \( i \neq j \), \( \text{Cov}(\epsilon_i, \epsilon_j) = \sigma_{ij} \), where \( \epsilon_i \) is the disturbance value in \( i^{th} \) observation:

\[
\rho_k = \frac{Y_k}{Y_0}
\]

(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:

\[
E(\mu) = \frac{2PN(P + N)}{(P + N)} + 1
\]

(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:

\[
\sigma^2 = \frac{2PN(2PN - P - N)}{(P + N)^2(P + N - 1)}
\]

(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:

\[
VR(k) = \frac{\sigma_k^2}{k\sigma^2}
\]

(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:

\[
VR(k) = 1 + 2 \sum_{j=1}^{k-1} (1 - \frac{j}{k})\rho(j)
\]

(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 \( M_t(k) \) is given by:

\[
M_t(k) = \frac{VR(x; k) - 1}{\phi(k)^2}
\]

(7)
The test statistic follows the standards asymptotically normal distribution, the asymptotic variance \( \Phi (k) \) can be given by:

\[
\Phi (k) = \frac{2(2k - 1)(k - 1)}{3k}
\]  

(8)

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

\[
M_2(k) = \frac{VR(x; k) - 1}{\Phi^*(k)^{1/2}}
\]  

(9)

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

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

(10)

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

(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 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).

**McLeod Li Test**

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”:

\[
Q(m) = \frac{n(n + 2)}{n - k} \sum_{k=1}^{m} r_d^2(k)
\]  

(12)

\[
r_d^2(k) = \frac{\sum_{t=k+1}^{n} e_t^2 e_{t-k}^2}{\sum_{t=1}^{n} e_t^2} \quad k = 0,1,...,n - 1
\]  

(13)

where squared residuals of autocorrelation are represented by \( r_d \), 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.

**Engle LM test**

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:
\[ \hat{\epsilon}_t^2 = \alpha_0 + \sum_{i=1}^{p} \alpha_i \hat{\epsilon}_{t-i}^2 + \nu_t \]  

(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:

\[ F \text{ statistic} = \frac{RRSS - URSS}{URSS} \times \frac{T - K}{m} \]  

(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 \(e[i, k]\)”. So that:

\[ v_{t,1} = r_{t-1}^2; \quad v_{t,2} = r_{t-1} r_{t-2}; \quad v_{t,3} = r_{t-1} r_{t-3}; \quad v_{t,k+1} = r_{t-2} r_{t-3}; \quad v_{t,k+2} = r_{t-2} r_{t-4}; \ldots; \quad v_{t,k} = r_{t-k}^2 \]  

(16)

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

While \(\gamma_1, \ldots, \gamma_k\) are computed through the following parameters of regression:

\[ r_{t-1} = \gamma_0 + \sum_{i=1}^{k} \gamma_i \hat{\nu}_{t,i} + \epsilon_t \]  

(17)

To testify that \(\gamma_1, \ldots, \gamma_k\) 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: William 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 \(\{x_1 \ldots x_n\}\) and history of \(m\) such as \(x_{mt} = (x_t, x_{t-1}, \ldots, x_{t-m+1})\), while for \(\epsilon\) distance and “embedding dimension (m)” the correlation integral \(\{C_m(n, \epsilon)\}\) can be computed as:

\[ C_m(n, \epsilon) = \frac{2}{(n-m)(n-m+1)} \sum_{S=1}^{n-m} \sum_{t=S+1}^{n-m+1} I_m(x_S, x_t, \epsilon) \]  

(18)
where the sample size is represented by $n$ while any two observations possess the maximum difference $\varepsilon$ for any embedded dimension $m$ which is calculated during computation of correlational-integrals. The test statistic of the BDS is:

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

where correlation integrals have a standard deviation of $\hat{V}_m$. With a normal distribution, $\sqrt{n} (C_m(n, \varepsilon) - C_1(n, \varepsilon)^m)$ is considered as a random variable in BDS test, when $n$ increases use $\varepsilon^* = 0.5 \sigma$, $1 \sigma$, $1.5 \sigma$ 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 subsamples. The lag orders up to 5 for autocorrelation coefficients are presented in columns 1-5. Results for the Runs test are presented in columns 6 and 7. While the very first column offers sample size, it is clear from the table that 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 periods.

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 1-5. Results for the Runs test are presented in columns 6 and 7. While the very first column offers sample size, it is clear from the table that 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 periods.

<table>
<thead>
<tr>
<th>Sample Period</th>
<th>Autocorrelation test</th>
<th>Runs Test</th>
</tr>
</thead>
<tbody>
<tr>
<td></td>
<td>1</td>
<td>3</td>
</tr>
<tr>
<td>COVID-19</td>
<td>0.501***</td>
<td>0.04***</td>
</tr>
<tr>
<td>Full-Sample</td>
<td>-0.511***</td>
<td>-0.026***</td>
</tr>
<tr>
<td>1977-1982</td>
<td>0.029***</td>
<td>-0.027***</td>
</tr>
<tr>
<td>1983-1994</td>
<td>0.005***</td>
<td>-0.005***</td>
</tr>
<tr>
<td>2001-2006</td>
<td>0.035</td>
<td>0.031</td>
</tr>
<tr>
<td>2013-2018</td>
<td>-0.524***</td>
<td>0.003***</td>
</tr>
</tbody>
</table>

Panel B: Metal

<table>
<thead>
<tr>
<th>Sample Period</th>
<th>Autocorrelation test</th>
<th>Runs Test</th>
</tr>
</thead>
<tbody>
<tr>
<td></td>
<td>0.521***</td>
<td>0.039***</td>
</tr>
<tr>
<td>Full-Sample</td>
<td>-0.511***</td>
<td>-0.026***</td>
</tr>
<tr>
<td>1977-1982</td>
<td>0.029***</td>
<td>0.049***</td>
</tr>
<tr>
<td>1983-1994</td>
<td>-0.034***</td>
<td>-0.039***</td>
</tr>
<tr>
<td>1995-2000</td>
<td>0.011</td>
<td>0.033</td>
</tr>
<tr>
<td>2001-2006</td>
<td>0.029</td>
<td>-0.035</td>
</tr>
<tr>
<td>2007-2012</td>
<td>0.03</td>
<td>0.029</td>
</tr>
<tr>
<td>2013-2018</td>
<td>0.042</td>
<td>0.003</td>
</tr>
</tbody>
</table>

Panel C: Oil

<table>
<thead>
<tr>
<th>Sample Period</th>
<th>Autocorrelation test</th>
<th>Runs Test</th>
</tr>
</thead>
<tbody>
<tr>
<td>COVID-19</td>
<td>-0.488***</td>
<td>-0.098***</td>
</tr>
<tr>
<td>Full-Sample</td>
<td>-0.499***</td>
<td>-0.01***</td>
</tr>
<tr>
<td>1983-1988</td>
<td>N/A</td>
<td>N/A</td>
</tr>
<tr>
<td>1989-1994</td>
<td>0.032</td>
<td>-0.132***</td>
</tr>
<tr>
<td>1995-2000</td>
<td>-0.002</td>
<td>-0.039***</td>
</tr>
<tr>
<td>2001-2006</td>
<td>0.001</td>
<td>0.027</td>
</tr>
<tr>
<td>2007-2012</td>
<td>-0.056</td>
<td>0.016</td>
</tr>
<tr>
<td>2013-2018</td>
<td>-0.091***</td>
<td>0.013***</td>
</tr>
</tbody>
</table>

Panel D: Silver

<table>
<thead>
<tr>
<th>Sample Period</th>
<th>Autocorrelation test</th>
<th>Runs Test</th>
</tr>
</thead>
<tbody>
<tr>
<td>COVID-19</td>
<td>-0.596***</td>
<td>-0.034***</td>
</tr>
<tr>
<td>Full-Sample</td>
<td>-0.509***</td>
<td>0.025***</td>
</tr>
<tr>
<td>1977-1982</td>
<td>0.156***</td>
<td>0.154***</td>
</tr>
<tr>
<td>1983-1988</td>
<td>-0.522***</td>
<td>0.02***</td>
</tr>
<tr>
<td>1989-1994</td>
<td>-0.513***</td>
<td>0.045***</td>
</tr>
<tr>
<td>1995-2000</td>
<td>-0.517***</td>
<td>0.014***</td>
</tr>
<tr>
<td>2001-2006</td>
<td>-0.507***</td>
<td>-0.022***</td>
</tr>
<tr>
<td>2007-2012</td>
<td>-0.01</td>
<td>0.003</td>
</tr>
<tr>
<td>2013-2018</td>
<td>-0.513***</td>
<td>0.015***</td>
</tr>
</tbody>
</table>

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-Stata package.
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 far 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.

70
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.

<table>
<thead>
<tr>
<th>Sample Period</th>
<th>VR Test</th>
<th>Ljung-Box Test before fitting AR model</th>
<th>Statistic</th>
<th>A</th>
<th>Ljung-Box Test after fitting AR model</th>
<th>Statistic</th>
</tr>
</thead>
<tbody>
<tr>
<td>K=4</td>
<td>K=16</td>
<td>Lag10</td>
<td></td>
<td></td>
<td>Lag20</td>
<td></td>
</tr>
<tr>
<td>COVID-19</td>
<td>0.287262**</td>
<td>0.073413**</td>
<td>68.787***</td>
<td>70.113***</td>
<td>0.2188</td>
<td>6.772***</td>
</tr>
<tr>
<td></td>
<td></td>
<td></td>
<td></td>
<td></td>
<td></td>
<td></td>
</tr>
<tr>
<td>Full-Sample</td>
<td>0.243***</td>
<td>0.060***</td>
<td>206.2***</td>
<td>208.9***</td>
<td>1.079</td>
<td>21.589</td>
</tr>
<tr>
<td>1983-1988</td>
<td>0.250***</td>
<td>0.062***</td>
<td>423.7***</td>
<td>423.7***</td>
<td>5.099</td>
<td>11.743</td>
</tr>
<tr>
<td>1989-1994</td>
<td>0.236***</td>
<td>0.061***</td>
<td>391.4***</td>
<td>403.4***</td>
<td>5.356</td>
<td>19.252</td>
</tr>
<tr>
<td>1995-2000</td>
<td>0.251***</td>
<td>0.058***</td>
<td>410.3***</td>
<td>429.5***</td>
<td>4.235</td>
<td>15.893</td>
</tr>
<tr>
<td>2001-2006</td>
<td>0.227***</td>
<td>0.062***</td>
<td>340.2***</td>
<td>345.6***</td>
<td>5.045</td>
<td>8.174</td>
</tr>
<tr>
<td>2007-2012</td>
<td>0.258***</td>
<td>0.065***</td>
<td>430.5***</td>
<td>431.0***</td>
<td>5.392</td>
<td>14.743</td>
</tr>
<tr>
<td>2013-2018</td>
<td>0.241***</td>
<td>0.060***</td>
<td>504.9***</td>
<td>511.0***</td>
<td>4.105</td>
<td>0.15</td>
</tr>
<tr>
<td>Full-Sample</td>
<td>0.257***</td>
<td>0.062***</td>
<td>204.5***</td>
<td>207.4***</td>
<td>0.019</td>
<td>7.273</td>
</tr>
<tr>
<td>1977-1982</td>
<td>0.266***</td>
<td>0.066***</td>
<td>428.4***</td>
<td>433.4***</td>
<td>3.043</td>
<td>17.039</td>
</tr>
<tr>
<td>1983-1988</td>
<td>0.254***</td>
<td>0.063***</td>
<td>494.1***</td>
<td>500.3***</td>
<td>8.023</td>
<td>5.376</td>
</tr>
<tr>
<td>1989-1994</td>
<td>0.238***</td>
<td>0.061***</td>
<td>418.8***</td>
<td>418.9***</td>
<td>9.211</td>
<td>16.767</td>
</tr>
<tr>
<td>1995-2000</td>
<td>0.255</td>
<td>0.059***</td>
<td>385.8***</td>
<td>393.8***</td>
<td>5.13.928</td>
<td>0.091</td>
</tr>
<tr>
<td>2001-2006</td>
<td>0.224***</td>
<td>0.060***</td>
<td>421.9***</td>
<td>442.8***</td>
<td>6.06</td>
<td>15.89</td>
</tr>
<tr>
<td>2007-2012</td>
<td>0.258***</td>
<td>0.064***</td>
<td>347.2***</td>
<td>352.6***</td>
<td>6.088</td>
<td>10.038</td>
</tr>
<tr>
<td>2013-2018</td>
<td>0.240***</td>
<td>0.060***</td>
<td>426.7***</td>
<td>427.0***</td>
<td>5.257</td>
<td>32.084</td>
</tr>
<tr>
<td>Full-Sample</td>
<td>0.254***</td>
<td>0.061***</td>
<td>199.0***</td>
<td>199.3***</td>
<td>9.007</td>
<td>6.525</td>
</tr>
<tr>
<td>1989-1994</td>
<td>0.257***</td>
<td>0.066***</td>
<td>346.1***</td>
<td>380.5***</td>
<td>3.024</td>
<td>15.054</td>
</tr>
<tr>
<td>1995-2000</td>
<td>0.252***</td>
<td>0.061***</td>
<td>350.0***</td>
<td>350.1***</td>
<td>10.035</td>
<td>14.579</td>
</tr>
<tr>
<td>2001-2006</td>
<td>0.252***</td>
<td>0.062***</td>
<td>362.2***</td>
<td>367.5***</td>
<td>7.1.147</td>
<td>34.838</td>
</tr>
<tr>
<td>2007-2012</td>
<td>0.231***</td>
<td>0.058***</td>
<td>415.4***</td>
<td>419.1***</td>
<td>1.263</td>
<td>12.236</td>
</tr>
<tr>
<td>2013-2018</td>
<td>0.230***</td>
<td>0.056***</td>
<td>475.1***</td>
<td>475.3***</td>
<td>10.0.027</td>
<td>11.261</td>
</tr>
<tr>
<td>Full-Sample</td>
<td>0.252***</td>
<td>0.061***</td>
<td>199.0***</td>
<td>200.4***</td>
<td>1.0.08</td>
<td>19.593</td>
</tr>
<tr>
<td>1977-1982</td>
<td>0.275***</td>
<td>0.067***</td>
<td>395.9***</td>
<td>402.6***</td>
<td>10.0.0258</td>
<td>7.507</td>
</tr>
<tr>
<td>1983-1988</td>
<td>0.265***</td>
<td>0.065***</td>
<td>429.2***</td>
<td>432.1***</td>
<td>9.11.447</td>
<td>0.215</td>
</tr>
<tr>
<td>1989-1994</td>
<td>0.248***</td>
<td>0.060***</td>
<td>412.4***</td>
<td>419.4***</td>
<td>1.0.16</td>
<td>20.229</td>
</tr>
<tr>
<td>1995-2000</td>
<td>0.254***</td>
<td>0.061***</td>
<td>419.0***</td>
<td>420.8***</td>
<td>1.15.688</td>
<td>0.025</td>
</tr>
<tr>
<td>2001-2006</td>
<td>0.257***</td>
<td>0.062***</td>
<td>402.7***</td>
<td>404.7***</td>
<td>2.0.031</td>
<td>9.757</td>
</tr>
<tr>
<td>2007-2012</td>
<td>0.257***</td>
<td>0.059***</td>
<td>406.8***</td>
<td>410.1***</td>
<td>3.0.194</td>
<td>8.846</td>
</tr>
<tr>
<td>2013-2018</td>
<td>0.238***</td>
<td>0.060***</td>
<td>412.1***</td>
<td>412.4***</td>
<td>1.0.08</td>
<td>10.086</td>
</tr>
</tbody>
</table>

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 subsample 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 nonlinear 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 sub-samples 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 sub-sample from 2013-2018 which exhibits

72
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.

<table>
<thead>
<tr>
<th>Sample-Period</th>
<th>AR</th>
<th>Engle LM Test-Statistic</th>
<th>Tsay Test-Statistic</th>
<th>McLeod-Li Test-Statistic</th>
</tr>
</thead>
<tbody>
<tr>
<td></td>
<td></td>
<td>Lag10</td>
<td>Lag20</td>
<td>Lag10</td>
</tr>
<tr>
<td>COVID-19</td>
<td>4</td>
<td>59.7***</td>
<td>88.3***</td>
<td>1.23***</td>
</tr>
<tr>
<td>Full-Sample</td>
<td>1</td>
<td>1466.2***</td>
<td>1525***</td>
<td>6.12***</td>
</tr>
<tr>
<td></td>
<td>5</td>
<td>143.1***</td>
<td>171.9***</td>
<td>2.10***</td>
</tr>
<tr>
<td>1989-1994</td>
<td>5</td>
<td>19.42</td>
<td>27.57</td>
<td>1.63***</td>
</tr>
<tr>
<td>1995-2000</td>
<td>4</td>
<td>52.3***</td>
<td>62.4***</td>
<td>2.50***</td>
</tr>
<tr>
<td>2001-2006</td>
<td>5</td>
<td>79.8***</td>
<td>86.6***</td>
<td>1.96***</td>
</tr>
<tr>
<td>2007-2012</td>
<td>5</td>
<td>100.1***</td>
<td>144.7***</td>
<td>1.78***</td>
</tr>
<tr>
<td>2013-2018</td>
<td>4</td>
<td>32.6***</td>
<td>39.8***</td>
<td>1.96***</td>
</tr>
<tr>
<td>COVID-19</td>
<td>6</td>
<td>70.9***</td>
<td>79.4***</td>
<td>1.53***</td>
</tr>
<tr>
<td>Full-Sample</td>
<td>8</td>
<td>1118.2***</td>
<td>1186***</td>
<td>4.17***</td>
</tr>
<tr>
<td>1977-1982</td>
<td>3</td>
<td>289.8***</td>
<td>296.5***</td>
<td>3.04***</td>
</tr>
<tr>
<td>1983-1988</td>
<td>8</td>
<td>137.6***</td>
<td>167.8***</td>
<td>1.93***</td>
</tr>
<tr>
<td>1989-1994</td>
<td>9</td>
<td>31.4***</td>
<td>37.1***</td>
<td>1.89***</td>
</tr>
<tr>
<td>1995-2000</td>
<td>5</td>
<td>45.6***</td>
<td>54.5***</td>
<td>1.90***</td>
</tr>
<tr>
<td>2001-2006</td>
<td>6</td>
<td>62.7***</td>
<td>69.2***</td>
<td>1.71***</td>
</tr>
<tr>
<td>2007-2012</td>
<td>6</td>
<td>94.6***</td>
<td>134.2***</td>
<td>1.80***</td>
</tr>
<tr>
<td>2013-2018</td>
<td>5</td>
<td>37.6***</td>
<td>43.5***</td>
<td>1.87***</td>
</tr>
<tr>
<td>COVID-19</td>
<td>5</td>
<td>32.5***</td>
<td>37.5</td>
<td>1.59***</td>
</tr>
<tr>
<td>Full-Sample</td>
<td>9</td>
<td>313.6***</td>
<td>346.2***</td>
<td>3.50***</td>
</tr>
<tr>
<td>1989-1994</td>
<td>3</td>
<td>50.4***</td>
<td>51.7***</td>
<td>6.49***</td>
</tr>
<tr>
<td>1995-2000</td>
<td>10</td>
<td>62.9***</td>
<td>89.0***</td>
<td>1.51***</td>
</tr>
<tr>
<td>2001-2006</td>
<td>7</td>
<td>22.6***</td>
<td>24.5</td>
<td>1.69***</td>
</tr>
<tr>
<td>2007-2012</td>
<td>1</td>
<td>386.3***</td>
<td>455.2***</td>
<td>2.94***</td>
</tr>
<tr>
<td>2013-2018</td>
<td>10</td>
<td>175.6***</td>
<td>195.3***</td>
<td>3.04***</td>
</tr>
<tr>
<td>COVID-19</td>
<td>3</td>
<td>123.0***</td>
<td>154.9***</td>
<td>2.43***</td>
</tr>
<tr>
<td>Full-Sample</td>
<td>1</td>
<td>771.7***</td>
<td>865.4***</td>
<td>2.56***</td>
</tr>
<tr>
<td>1977-1982</td>
<td>10</td>
<td>268.4***</td>
<td>289.7***</td>
<td>2.03***</td>
</tr>
<tr>
<td>1983-1988</td>
<td>9</td>
<td>133.4***</td>
<td>154.9***</td>
<td>1.74***</td>
</tr>
<tr>
<td>1989-1994</td>
<td>1</td>
<td>146***</td>
<td>176.0***</td>
<td>3.45***</td>
</tr>
<tr>
<td>1995-2000</td>
<td>1</td>
<td>20.1***</td>
<td>37.8***</td>
<td>1.049</td>
</tr>
<tr>
<td>2001-2006</td>
<td>2</td>
<td>146.1***</td>
<td>158.8***</td>
<td>2.43***</td>
</tr>
<tr>
<td>2007-2012</td>
<td>3</td>
<td>109.0***</td>
<td>135.9***</td>
<td>2.24***</td>
</tr>
<tr>
<td>2013-2018</td>
<td>1</td>
<td>75.1***</td>
<td>78.4***</td>
<td>2.06***</td>
</tr>
</tbody>
</table>

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 efficiency) 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


